Improving Supply Chain Planning in a Competitive Environment

Miguel A. Zamarripa[a], Adrián M. Aguirre[b], Carlos A. Méndez[b] and Antonio Espuña[a]

[a]*Universitat Politècnica de Catalunya (UPC), Chem. Eng. Dpt., Barcelona, Spain*

[b]*INTEC (UNL-CONICET), Santa Fe, Argentina*

Abstract

This work extends the use of a Mixed Integer Linear Programming (MILP) model, devised to optimize the Supply Chain planning problem, for decision making in cooperative and/or competitive scenarios, by integrating these models with the use of the Game Theory. The system developed is tested in a case study based in previously proposed Supply Chain, adapted to consider the operation of two different Supply Chains (multi-product production plants, storage centers, and distribution to the final consumers); two different optimization criteria are used to model both the Supply Chains benefits and the customer preferences, so both cooperative and non-cooperative way of working between both Supply Chains can be considered.

Keywords: Supply Chain planning, MILP-based model, Game Theory, Competitive Supply Chains.

1. INTRODUCTION

The problem of decision making in the process industry is becoming more complex as the scope covered by these decisions is extended. This increasing complexity is additionally complicated by the need to consider a greater degree of uncertainty in the models used to forecast the events that should be considered in this decision making. In the case of the Chemical Processes Industry, the complexity associated to chemical operations and the market globalization should be added to the usual difficulties related to the integration of various objectives to be considered. So, in this sense, the problem of decision making associated to Supply Chain (SC) tactical management (procurement of raw materials in different markets, allocation of products to different plants and distributing them to different customers), which has attracted the attention of the scientific community in the last years, is on the top level of complexity.

During the last two decades, an increasing number of works published in academic literature address this kind of decision-making problems, dealing with the coordination of inventory, production and/or distribution tasks. A significant number of these works face the production planning problem of multiple products in SCs or more complex production networks including production-distribution options, some of them considering MILP models for their optimization, taking into account different or even multiple objectives (Wilkinson *et al.*, 1996; McDonald and Karimi, 1997; Gupta and Maranas, 2000; Jackson and Grossman, 2003; Neiro and Pinto, 2004; Hugo and Pistikopoulos, 2004). But it is not easy to find works that simultaneously address the three main tasks (inventory, production and distribution) involved to optimize SC planning problem, specially for the case of more general operation networks including, for example, multipurpose path ways, combination of different intermediate storage policies, task changeovers management, etc. (McDonald and Karimi, 1997). Additionally, as already stated in Shah (2005), the industries are facing new challenges, including changes in the orientation of their business policy, which is moving from product-oriented to service-oriented processes, due to the increasing dynamism and competition of the markets, whose main goal is to receive high value added products at commodity costs and services. As a result, the most typical SC's planning models should consider backorder and subcontracting actions for intermediate and final products, as been suggested by Kuo and Chang (2007). However, the current economic situation is leading, in some cases, to a drastic reduction in the market's demand, while the production capacity level is, in general, maintained.

In this framework, most of the recent work devoted to improve the decision making strategies associated to SC Management (SCM) at the planning level is focused to analyze and solve the problems associated to one or more of the following generic open issues (see Figure 1).

Figure 1. Open issues to improve Supply Chain decision making.

Vertical integration: The need to ensure coherence among different decisions, usually associated to different time and economic scales, is one of the main complicating elements to model and solve the SC planning problem. In this sense, some current approaches are based on the development of design-planning models (Laínez *et al.*, 2009), while others are focused on the integration of low decision levels as planning-scheduling models (Sung and Maravelias, 2007; Guillén *et al.*, 2005).

Simultaneous consideration of multiple objectives: market, social and other external or internal pressures currently justify the introduction of individual elements related to environmental, risk, customer satisfaction and other considerations as the SCM objectives, at the same level as other traditional indicators based on the economic performance. The need to consider the resulting trade-offs among these different objectives transforms the way to deal with the decision making problem (Bojarski *et al.*, 2009; Guillén and Grossmann, 2010).

Uncertainty management: one basic characteristic of the SC planning problem, as already indicated, is the presence of uncertainty affecting the "here and now" decision making. This uncertainty may affect the availability of production resources, the raw materials supply, the operating parameters (lead times, transport times, etc.) and/or the market scenario (demand, prices, delivery requirements, etc.). A literature review on this topic reveals that most of the systematic tools currently available to manage decision making under uncertainty have been proposed to deal with this SCM issue: Model Predictive Control (Bose and Penky, 2000), Multi-Parametric Programming (Wellons and Reklaitis, 1989; Dua *et al.*, 2009) and Stochastic Programming (Gupta and Maranas, 2003; Haitham *et al.*, 2004; You and Grossmann, 2010; Amaro and Barbosa-Póvoa, 2009).

Finally, market globalization imposes the need to consider some of the above mentioned elements from a new perspective: new objectives should be considered, different from the ones typically applicable to the individual SC echelons, like financial aspects (Laínez *et al.*, 2007; Guillén *et al.*, 2005). Also the market uncertainty should be managed taking into account the roles of many different players, and the vertical integration should include a much larger scope. Within this scope, studying the problems that industry deals with and applying fast and reliable optimization techniques to find isolated robust solutions is not enough: SCs are embedded in a competitive market, and managers have to take care of the decisions made by third parties (known or uncertain), since these decisions will impact on the profit of their own SC.

This complex scenario is specifically addressed by the Game Theory (GT), to analyze the eventual success of some decisions among other alternatives. This approach has been widely proposed by researchers and practitioners to develop systematic procedures to assist decision-makers (Nagarajan and Socîs, 2008; Cachon, 2004).

The different concepts describing the GT and its application to solve industrial decision making problems can be easily found in literature. It is worth to remark here that one of the first steps is to characterize the scenario where the GT is applied, starting with the identification of two opposite types of game: the cooperative game (all players share a common objective) and the non-cooperative game (each player has an individual objective, which usually will not coincide with the objective of the rest of players). It is also important to define the concept of equilibrium, associated to a situation in which no player has nothing to gain by changing only his own strategy unilaterally, if the other players keep their own strategy unchanged (Nash equilibrium, Nash, 1950), stressing the fact that the optimal strategy in a non-cooperative game depends on the strategies of the other players. In fact, the industrial practice is not so simple. Equilibrium will be always a utopian situation and elements of both types of game can be simultaneously found in situations like the ones described in the previous paragraphs.

This and many other practical problems cause that nowadays only some aspects of the GT have been successfully applied to SCM. It is easy to find applications related to simple non-cooperative games, while the use of complex games (i.e.: dynamic or asymmetric games) for decision making has not been exploited yet (Cachon and Netessine, 2004). In this sense, there are no many works in which GT has been extensively used to analyze the behavior between different SCs and only a few works address the SC planning problem in very specific situations. Among them, it is worth to mention the work of Leng and Parlar (2010), proposing the use of Nash and other related equilibrium concepts to determine optimum production levels of a single SC, playing different scenarios to fix the price between seller and buyer. Previously, this kind of games had been successfully applied to solve this kind of problems by other authors (Cachon, 2004; Granot and Yin, 2008; Leng and Zhu, 2009; Wang, 2006), each one using different techniques from the GT. Cachon and Zipkin (1999) also solve a two-stage single SC problem, considering backorder penalty cost, inventory cost and transportation times based on the inventory management.

There are many useful concepts/policies related to decision-making optimization in cooperative/competitive games which can be applied to SCM, but obviously this paper does not intend to review all of them. Specifically, the objective of this paper is to set the basis of a SC planning support system capable of explicitly considering the presence of other SCs, so as to reduce the uncertainty usually incorporated to the demand forecasting model used for decision making. Then, the focus of the analysis of cooperative games in this work is related to the targeting of the overall profit which can be reached through the cooperation among several SCs, while each SC makes decisions to maintain their production, storage and distribution capacity. On the contrary, in the case of non-cooperative games, the main objective is the identification of the way to adapt the market share to get the maximum benefits from the specific working scenario.

Other topics to be analyzed through the use of the GT may include negotiation, profit sharing and alliance formations. For example, Greene (2002) indicates how several instances of alliances between component manufacturers in the semiconductor industry may improve the overall benefit and their relative negotiation position, which is affected by changes in the sharing market policies. For a comprehensive analysis of the issues related to these topics, the interested reader is addressed to specialized literature, like the work of Nagarajan and Socîs (2008). In the same way, another important result to be obtained from the use of the GT in cooperative games is the analysis of the profit/cost allocation for general SC networks. For the discussion of the framework and theoretical issues associated to this analysis, the interested reader is referred to the book of Slikker and Van den Nouweland (2001).

Figure 2 summarizes the bases of the use of the GT as an optimization tool to manage uncertainty, playing both cooperative and non-cooperative games. Its application is easy to understand since the basic concepts of the GT (introduced in the next sections) are very intuitive.

Figure 2. Use of the Game Theory as a tool to manage SC under uncertainty.

In any case, it is also important to note at this point that the SC business analysis through the use of the concepts associated to the GT will commonly lead to negotiation, in terms of prices established for sellers and buyers, contracting and profit sharing issues, quantities to be delivered, delivery schedules, etc. A way to model this negotiation consists in the use of bargaining tools. For example, Kohli and Park (1989) study how the buyer and seller negotiation lead to discounts in the contracts, and Reyniers and Tapiero (1995) use a cooperative model to study the effect of prices in the suppliers and producers negotiations.

This work is focused on the systematic consideration of some of the above mentioned elements (open issues) in the SC planning problem, where decisions are inventory, production and distribution management, and a global market scenario should be considered, targeting the benefits and drawbacks of the eventual cooperative work with other SCs, and also their eventual competition. The next section includes a formal introduction to the SC planning problem and to the GT as optimization tool, as well as the main elements of the considered model. Then, Section 3 illustrates the combined application of these elements and tools to a specific case study, based on an example proposed in literature, and Section 4 summarizes the main conclusions of this study.

2. The Supply Chain planning problem

The typical scope of the SC planning problem is to determine the optimal production levels, inventories and product distribution in an organized network of production sites, distribution centers, consumers, etc. (Figure 3), taking care of the constraints associated to products and raw materials availability, storage limits, etc. in such network nodes. The mathematical model associated to this problem usually leads to a mixed-integer linear program (MILP) whose solution determines the optimal values for the mentioned variables.

Figure 3. Typical SC Network configuration.

In this paper it will be assumed the existence of a set of different Supply Chains that may work in a cooperative or a competitive environment. The model originally proposed by Liang (2008) has been adopted as a basic model for the presented mathematical formulation, complemented with additional constraints and different Objective Functions according to the considered scenario. In this case, the mathematical constraints associated to the material balances and production/distribution capacities will be the same, as well as the cost structures. A discrete time formulation, which also integrates SCM decision levels, by considering a higher level planning model, with a cyclic time horizon, usually employed to solve this kind of models (Liang, 2008; Sousa *et al.*, 2008), has been adopted in this work.

So, in summary, the logistic network considered in this model consists of several SCs, each one composed by multiple production sites and distribution centers (fixed locations and capacities). Production sites are able to produce several products to cover a common market demand over a planning horizon *H*. The capacity of each process is given by available labor levels and equipment capacity for each production site, and the transport between nodes is modeled as a set of trucks with fixed capacity, in which costs and required transporting times are related to the distance between nodes. The planning horizon H is discretized in medium term planning periods, as months.

2.1 Cooperative and non-cooperative Games

In a non-cooperative scenario, the different organizations are not allowed to make commitments regarding their respective strategies; instead they are competing to get their maximum individual benefit. In the opposite way, cooperative scenarios are associated to the possibility to arrange such commitments, which are dealing with side-payments and/or other compensation agreements among organizations. In this work, it has been assumed that this second scenario will lead to a perfect integration between SCs when the cooperative game is played. Then, the complete set of SCs will try to minimize the total aggregated cost to achieve the demand of the consumers. The competition behavior will be found when each individual SC tries to maximize its individual benefit and the consumers buy from the cheaper SC.

2.1.1 Supply Chain planning in a cooperative environment

On the basis of above definitions, it is proposed the application of a multipurpose MILP-based model for the cooperative case of SCs, equivalent to the one which should be formulated to solve one individual SC. So, in order to determine the optimal production planning and distribution decisions, a slightly modified version of the formulation proposed by Liang (2008) has been used.

Then, the SC management performance is characterized by the quantities produced at each source Q_{inh}, the inventory levels W_{inh}, the undelivered orders E_{inh} and the quantities arriving to each distribution center T_{inhj},. The detailed definition of the different variables and parameters is included in the notation section.

The same final condition assumed in the work of Liang (2008) is considered, imposing that there is not storage at the end of the time horizon. However, in order to better compare the different scenarios studied in this work, the subcontracting service introduced in the original work of Liang (2008) has not been implemented.

2.1.1.1 Objective function

Eq. (1) represents the total operating cost of the SC of interest (in case of a cooperative game, the aggregated one, composed by the whole set of echelons of the individual SCs), resulting from adding the production, inventory, backorder and transportation costs of each echelon to be considered.

Since the original model proposed by Liang (2008) considers a bi-objective optimization, the second objective has been maintained for comparison purposes (Eq. 2). This second objective represents the accumulated delivery time from the different production echelons to the distribution nodes, and so it is somehow parallel to the fourth term of the first considered objective (Eq. 1).

$$\min_{g} z1 = \sum_{i \in I_{G(g)}} \sum_{n=1}^{N} \sum_{h=1}^{H} a_{in} Q_{inh} (1+e_b)^h + \sum_{i \in I_{G(g)}} \sum_{n=1}^{N} \sum_{h=1}^{H} c_{in} W_{inh} (1+e_b)^h + \sum_{i \in I_{G(g)}} \sum_{n=1}^{N} \sum_{h=1}^{H} d_{in} E_{inh} (1+e_b)^h + \sum_{i \in I_{G(g)}} \sum_{n=1}^{N} \sum_{h=1}^{H} \sum_{j=1}^{J} k_{inj} T_{inhj} (1+e_b)^h \quad (1)$$

$$z2 = \sum_{i \in I_{G(g)}}^{I} \sum_{n=1}^{N} \sum_{h=1}^{H} \sum_{j=1}^{J} [\frac{u_{inj}}{s_{inhj}}] T_{inhj} \quad (2)$$

2.1.1.2 Constraints

The basic mass balances to be established along the different SC echelons must be considered in the model. Eq. (3) applies this balance at the first time period, considering the initial inventory, production, distribution and resulting inventory levels, while Eq. (4) is applicable to the subsequent time periods. Finally, the total demand satisfaction is enforced (Eq. 5).

$$II_{in} + Q_{in1} - \sum_{j=1}^{J} T_{in1j} = W_{in1} - E_{in1} \qquad \forall\ i, n \quad (3)$$

$$W_{inh-1} - E_{inh-1} + Q_{inh} - \sum_{j=1}^{J} T_{inhj} = W_{inh} - E_{inh} \qquad \forall\ i, n \quad \forall\ h > 1 \quad (4)$$

$$\sum_{i=1}^{I} T_{inhj} \geq Djj_{nhj} \qquad \forall\ n, h, j \quad (5)$$

The production is limited by the labor level capacity, as it expressed in Eq. (6) and also by the unit's capacity, stated in Eq. (7). An available budget capacity for each Supply Chain *g* and a maximum storage capacity at each Production plant *i* have been also considered in Eq. (8) and Eq. (9).

$$\sum_{n=1}^{N} l_{in} Q_{inh} \leq F_{ih} \qquad \forall\ i, h \quad (6)$$

$$\sum_{n=1}^{N} r_{in} Q_{inh} \leq M_{ih} \qquad \forall\ i, h \quad (7)$$

$$z1(g) \leq Bdd(g) \quad \forall\, g \tag{8}$$

$$\sum_{n=1}^{N} vv_n W_{inh} \leq Rdd_{h,i} \quad \forall\; h\,, i \tag{9}$$

In order to reproduce a more realistic situation, distribution capacities per period, from each source *i* to each end point *j*, are limited to a certain range, as it showed by Eq. (10). In the same way, also minimum and maximum production capacities per period at each production center have been considered in Eq. (11).

$$X_{inhj} Mind_{in} \leq T_{inhj} \;\leq\; X_{inhj} Maxd_{in} \quad \forall\; i\,, n\,, h\,, j \tag{10}$$

$$Y_{inh} Minp_{in} \leq Q_{inh} \;\leq\; Y_{inh} Maxp_{in} \quad \forall\; i\,, n\,, h \tag{11}$$

2.1.2 Non-cooperative Game Theory

The application of the non-cooperative GT is based on the simulation of the results obtained by a set of players ($i = 1, ..., I$) following different strategies (S_n; $n = 1, ..., N$). These results are represented through a sort of payments ($P_{i,n}$; $i=1…I$; $n=1…N$) received by each player. In simultaneous games, the feasible strategy for one player is independent from the strategies chosen by each of the other players. Optimum strategies depend on the risk aversion of the players, so different strategies can be foreseen, as for example max-min strategy (which maximizes the minimum gain that can be obtained). Depending on the knowledge about the strategy of the other players, other solutions resulting from the concept of Nash equilibrium can be devised.

Two alternative scenarios should be considered, which in the GT are usually identified as zero-sum and nonzero-sum games. In the zero-sum game, it is impossible for the two players to obtain a global benefit from their cooperation because the amount gained by one player is the amount lost by the other player. On the other hand, in the non zero-sum game, it is impossible to deduce the player’s payoff from the payoff of the others; the nonlinearities of the problem also arise in this second kind of games.

This work assumes that the problem can be classified as a non zero-sum game. This characteristic, and the fact that the SC of interest tries to maximize its own benefit disregarding the overall benefit of the system, lead to an optimization procedure based on the computation of a payoff matrix. Such matrix is made up by the assessment of different potential strategies of the players, and it shows the behavior for each action of the SC against the actions of its competitors. If the computation of this payoff matrix ensures that it is composed by the different Nash Equilibrium points, as previously defined, the problem solution will be reduced to find the optimum performance resulting from this payoff matrix.

To play this game, each SC (player) should deal with the demand that customers really offer to it (part of the total demand), and it has been assumed that this can be computed from the SC service policy (prices and delivery times), compared to the service policy of the rest of SCs. The way how each SC decides to modify this service policy has been modeled through its price rate ($Prate_g$), representing eventual discounts or extra costs that SCs may apply. A nominal selling price (Ps_{inj}) has been also introduced to maintain data integrity. So, additionally to the operating cost of the SCs (*z1*, Eq. 1, which already incorporates the objective to maintain the delivery due dates), it is necessary to introduce a new objective based on the reduction of the buyers' expenses (cost for the distribution centers) associated to the different $Prate_g$: the consumers (distribution centers) will try to obtain the products from the cheaper Production Plant (of the corresponding SC).

$$Min\ CST(g) = \sum_{i \in I\_G(i,g)} \sum_{n} \sum_{h} \sum_{j} Ps_{inj} T_{inhj}\, Prate_g + z1(g) \qquad \forall\ g \tag{12}$$

In order to modeling better the demand behavior, a price elasticity of the demand has been also considered (see Eq. 13). So *Ed* is proposed to indicate the sensitivity of the quantity demanded to the price changes (Varian, 1992):

$$Ed = \frac{\Delta D / D}{\Delta P / P} \tag{13}$$

Then, Eq. (14) computes the new demand to be satisfied by the set of SCs, based on the original demand satisfaction, the discount rates and the price elasticity of the demand.

$$Dem_{nhj} = \max_{g} \left[Djj_{nhj} - Ed\ Djj_{nhj} \left(\frac{Prate_g}{100} \right) \right] \qquad \forall\ n, h, j \tag{14}$$

Again, it is assumed that the total demand should be fulfilled.

$$\sum_{i} T_{inhj} \geq Dem_{nhj} \qquad \forall\ n, h, j \tag{15}$$

2.2 General solution strategy

The cooperative problem is formulated as a MILP model by Eq. (1) and (3-11), and will be solved trying to minimize the total cost *z1* (sum of production, inventory, backorder and transportation costs, Eq. 1) of the aggregated Supply Chain SC (SC1+SC2+…SCn).

The competitive problem is solved through the evaluation of the payoff matrix, which is constructed from the computation of the individual performance associated to each one of the feasible strategies for each player considered in the game. This performance is obtained by running an MILP competitive model for each of the scenarios considered (see Table A.1). The MILP competitive model is constructed using Eqs. (3), (6-11), and (14-15), and it is solved to also consider the expense of the buyers, in Eq. (12).

Also, delivery time of the products to the distribution centers *z2*, in Eq. (2), and the benefit (difference between sales and total cost) of each SC can be computed to highlight the different results obtained in the cooperative and competitive environments.

3. CASE STUDY: RESULTS AND DISCUSSION

These concepts have been applied to a Supply Chain case study adapted from Wang and Liang (2004, 2005), and Liang (2008). The basic SCs configuration considered is composed by 2 SCs (2+2 plants, Plant1/Plant2 and Plant3/Plant4) which collaborate or compete (according to the considered situation) to fulfill the global demand from 4 distribution centers. Two products, P1 and P2, and the market's demand at the distribution centers for 3 monthly periods of these products are considered in Table A.3. In all cases, the factories' strategy is to maintain a constant work force level over the planning horizon, and to supply as much product as possible (demand), playing with inventories and backorders. The information about the considered scenarios, production, etc. and the rest of problem conditions (initial storage levels, transport capacities, etc. and associated costs) can be found in Appendix A (Tables A.1-A.4).

Figure 4. Description of the SC Network. Plants1-4 serve Distr1-4.

In order to enforce a fair collaboration and/or competence among the 2 considered SCs, the same labor levels, production capacities, production costs and initial inventories have been considered also for Plant 3 and Plant 4 respectively (Tables A.5 and A.6). The proposed geographical distribution for Plants 1-2 and Distribution centers 1-4 are coherent with the transport times and costs proposed in the original case study. Plants 3 and 4 have been incorporated as represented in Figure 4, and transport times and costs have been calculated (second term in Table A.4) to be coherent with this representation. Finally, transport costs related to all the distribution tasks (first term in Table A.4) have been modified respect to the original data by a factor of 10, in order to get more significant differences in the obtained results (competitive/cooperative policies), and facilitate the discussion of these differences.

Since the overall production capacity of the system now described (Plants 1 to 4) is double than the one considered in the original problem (Plants 1 and 2), two levels of market demand that have to be satisfied by the distribution centers will be analyzed in the next section. For the initial comparisons, the original demand will be considered (so both SCs are oversized if they are assumed to share the market demand); in order to compare cooperative and competitive scenarios, double demand is assumed. In this later case, the global capacity will be on the line of the global demand, and additional budget and storage limits in the SCs will be considered. The price elasticity of the demand has been assumed to be (*Ed*= -5.0).

The resulting MILP model has been implemented and solved using GAMS/CPLEX 7.0 on a PC Windows XP computer, using an Intel ® Core™ i7 CPU (920) 2.67 GHz processor with 2.99 GB of RAM. The mathematical model for the specific case study consists of 381 equations, involving 311 continuous variables and 288 discrete variables, requiring an average computational time of 0.078 seconds to be solved with a relative gap of 0%. In the competitive behaviour, the model dimensions are very similar, although the problem has been solved for the different considered scenarios (payoff matrix).

3.1 Case study results

In order to highlight the main potential benefits of the proposed approach, several production scenarios have been solved:

Tables 1 and 2 summarize the results obtained considering a standalone situation: SC1 and SC2 have been independently optimized to fulfill the demand levels originally proposed by Liang (2008). In Table 1, the results originally reported by Liang (2008) are also included.

Table 1. Comparative results between SCs (standalone cases).

Optimal solutions for SC1 or SC2 (in the standalone case of original demand) are driven by the geographical conditions (nearest delivery, as it can be observed in Figure 4), although different solutions would be obtained for each SC depending on the specific objectives considered. Detailed results can be found in Figure 5 (production levels for each product at each production center), Figure 6 (inventory levels), and Table 2, which summarizes the expected distribution tasks (product deliver from Production Plant *i* to the Distribution center *j* at each time period *h*). Obviously, the significant differences between SC1 and SC2 standalone solutions are originated by the different geographical situation of their production sites vs. the distribution centers, and it is worth to emphasize that, although in the case of SC2, the production load is clearly much better balanced between its 2 production centers, while SC1 exhibits a lower total operating cost (see Table 1). This behavior is consequence of the specific circumstances considered in this case-study: Plant 1 is located in a privileged geographical situation, and work load unbalance is not penalized unless it implies storages and/or delays. So the main policy for SC1 is to assign as much demand as possible to Plant1. At the specific demand levels considered in this case study, this can be done without incurring in storage/delay penalties, and the risk to suffer higher costs to accommodate additional demands from distribution centers (Distr2, Distr3 or Distr4) is not penalized either. Obviously, other production and/or storage costs would lead to other production/distribution policies, resulting in global performances which probably will be also significantly different.

Figure 5.Optimal Production levels (Q_{inh})

Figure 6. Optimal Inventory levels (W_{inh}).

Table 2. Optimal Distribution planning for SC1 and SC2.

Table 3 shows different results obtained when both considered SCs are working together in a common scenario. As it was expected, the optimal solution for SC1 when coexisting with SC2 depends on the kind of relation (cooperative/competitive) with its counterpart and its capacity to adopt different commercialization policies, in this case represented just by the selling prices it can offer to each distribution center.

In the cooperative case (Table 3a) the overall SCs costs (z1 associated to the aggregated SC, Eq. 1) are obviously reduced with respect to both standalone situations (Table 1), although the general rules leading to the optimum production/distribution policies are the same: to reduce the distribution costs, since the other costs are considered identical.

Table 3. Comparative results between SCs (cooperative/competitive scenarios).

For the competitive case, the decision should take into account the consumers' preferences, as previously identified (CST, Eq. 12), and the equivalent results are summarized in Table 3b. In this case, if the demand is considered at its original level (consequently, both SCs would be oversized in a factor of 2), both SCs are able to play the competitive game maintaining their respective geographical influence. But when the demand is approaching to the SCs global capacity, a proper pricing policy is basic to reduce the losses associated to competition: The capacity to manage the selling prices assumed by SC1 allows increasing its benefit (even assuming larger costs) at the expenses of SC2. As the Game Theory states, the payoff matrix exhibits multiple Nash equilibrium points, since for each scenario in the competitive behaviour, the SC of interest exhibits multiple alternatives to improve the decision and to obtain the best solution in the payoff matrices (see Table 4 for the original demand situation, and Table A.7 for the double demand case study). The solution shown in Table 3b corresponds to the best of these Nash equilibrium points: The SC1 selling price is computed in such a way that further reductions on the selling price of SC2 will not modify the choice of the buyers or, if so, this will not increase SC2 benefits.

Cachon (1999) states that usually the competitors choose wrong policies and do not optimize the overall SC performance due to the externalities of such change of policies: the action of one SC impacts to the other SCs, but this does not modify the competitors' policies. The proposed approach is robust in this sense: the solution based on the analysis of the payoff matrix supports these externalities, since the SC of interest is able to choose the best solution analyzing the expected reactions of the other SCs. For example: if the objective was to improve the decision making of the SC1 for the scenario 1 of SC2, the Nash equilibrium point would be the one reported in Table 3b for the original demand, because this is the best solution of the problem(when SC1 obtains the maximum profit) for that scenario of SC2. However, if the objective was to improve the decision of the SC2 when SC1 plays the scenario 1, the Nash equilibrium point would be the scenario 5 (discount of 0.4%) of SC2, which represents its maximum benefit as shown in Table 4.

Table 4. Payoff matrix for the competitive case (original demand).

3.2 Bargaining tool

Several works presented in the field of SC planning discuss the importance of considering the eventual reactions of the different SCs, especially for the cooperative case. Alliances setup, based on a given level of demand along the SC, trying to select partners that give an added value to the resulting SC (Gunasekaran *et al.*, 2008) is a main strategic objective. Mentzer *et al.* (2001) establishes that the success of the cooperation is guaranteed if the SCs have the same goal and the same focus on serving customers.

Given the present economic situation, the approach presented in this work can be used as a Bargaining Tool in both cooperative and competitive SC market scenarios. In this sense, Figure 7 (Cost analysis) shows the total production, inventory and distribution costs for the different studied scenarios. As it can be observed there, SC1 costs slightly less to operate (<1%) than SC2; also analyzing SC1 vs. SC2 in the cooperative case (SC1 - SC2 coop.) it can be observed that an overall cost improvement of about 4% can be achieved when both SCs work together. Also, the scenarios identified during the discussion of the competitive cases, corresponding to the Nash equilibrium of the payoff matrix, have been represented in Figure 7 (best result when playing as SC1 and best result when playing as SC2). As it can be seen there, SC1 keeps being cheaper for the competitive cases. Disregarding the effects of the geographical situation of the corresponding production facilities, these results can be also used to identify improvement opportunities: in this specific case, a minimum change in the production costs will lead to a dramatic change in the competition scenario, since these costs represent the highest expenses of any SC. Also, the introduction of commitments between SCs and customers would significantly modify the problem conditions, reducing the pressure to get the highest market share, which might also lead to completely different production/distribution SC policies.

But probably the most important benefit of this kind of studies would be the possibility to use the overall information computed during the optimization procedure to negotiate agreements with the distribution centers and/or the competing partners. For example: in the proposed case-study SC2 generates the 36% of the total benefits in the optimal cooperative situation, but it would only generate the 15% of the benefits in the best solution proposed by SC1, even it might get the 66% of the benefits in the best competitive solution to be proposed by the same SC2. This information can be used both directly, or associated to other elements identifying additional trade-offs (for example, related to product quality, service reliability, etc.), in order to arrange new agreements aiming to modify an economically unbalanced situation.

Figure 7. Cost Analysis for the studied examples

4. CONCLUSIONS

Current state of the art in the area of SC planning considers the optimization of a single SC model facing a distributed demand which follows an uncertain behavior. But actually, this behavior results from the combination of two factors: the uncertainty on the demand itself and, in the common case in which other suppliers are available, the consumers' preferences. It is well know that decoupling these two elements may allow a more comprehensive tactical decision-making, but this fact has been rarely exploited to develop systematic optimization approaches in this field.

This paper analyzes the combined use of mathematical programming based optimization and Game Theory as an effective way to solve SC planning problems in competitive/collaborative scenarios. The planning is performed under competition uncertainty, so changes in the competition behavior are explicitly contemplated; the resulting solutions can be considered as a bargaining tool between SCs. This is achieved through the use of the pay-off matrix as decision tool to determine the best playing strategy among previously optimized SC decision-making (production, inventory and distribution levels in a deterministic scenario).

This inner problem (optimum SC management) is modeled using a MILP-based approach. In order to specifically take into account the considered situation (several SCs working simultaneously) some changes have been introduced in the usual problem formulation with respect to the regular way of representing the objectives, the variables and the constraints usually associated to the SC management problem (which might also consider some other endogenous or exogenous sources of uncertainty).

Then, the proposed mathematical programming formulation of the model (including the incorporation of specific terms in the objective function) and the use of the GT have allowed considering the competition behavior between SCs showing uncertain behavior. In this sense, this way of managing demand uncertainty offers the advantage that the solution for each scenario represents the optimal solution for the problem (considering each scenario as a problem), and so the optimality of the proposed solution can be guaranteed based on the knowledge of the position of the competitors (reactive approach: the solution is adjusted to the changes in the competition scenario).

Additionally, SC managers should also consider negotiation with competitors, providers and clients. In this negotiation, issues like contracting, profit sharing, or delivery schedules should be considered. This paper presents a logical approach to systematically analyze these issues, characterizing the presence of these competing SCs as a source of uncertainty linked to the demand uncertainty to be considered when looking for a robust SC Management. The results allow to quantify the importance of considering different Supply Chains as competitors and/or collaborators in terms of total cost, customer satisfaction, environmental impact (including distribution actions), and cost for the consumers.

Further work in this line includes the development as a proactive approach (robust decision making without previous knowledge about the competitors behavior), as well as the incorporation of additional elements to be considered in the objective function (multi-objective approach).

Notation

Indexes and sets:

n	Products (*n*=1,2, …, *N*)
i	Production sites(“sources”, *i*=1,2, …, *I*)
h	Time periods (*h*=1,2, …, *H*)
j	Distribution centers(*j*=1,2, …, *J*)
g	Supply Chain(*g*=1,2, …, *G*)
I_G(g)	Production sites *i* belonging to Supply Chain *g*.

Parameters:

a(i,n)	Production cost per unit of product *n* produced at source *i* ($/unit)
c(i,n)	Inventory - cost per unit of product *n* at source *i* ($/unit)
d(i,n)	Backordering cost per unit of product *n* at source *i* ($/unit)
l(i,n)	Hour of work per unit of product *n* produced at source *i* (man-hour/unit)
r(i,n)	Required equipment occupation per unit of product *n* at source *i* (machine-hour/unit)
vv(n)	Warehouse space required per unit for product *n* (ft^2/unit)
k(i,n,j)	Transport cost per unit of product *n* from the source *i* to the endpoint *j* ($/unit)

u(i,n,j)	Transport time of product *n* from source *i* to end point *j* (hour/truck)
s(i,n,h,j)	Capacity per truck for product *n* from source *i* to endpoint *j* (units/truck)
Rdd(h,i)	Maximum storage space at production plant *i* in period *h* (units)
M(i,h)	Maximum machine level available at source *i* in period *h* (machine-hour)
F(i,h)	Maximum labor level of work at source *i* in period *t* (man-hour)
Djj(n,h,j)	Nominal demand of product *n* in period *h*at endpoint *j* (units)
Dem(n,h,j)	Demand of product *n* in period *h* at endpoint *j* according to the considered price elasticity of the demand (units)
Bdd(g)	Total Budget for Supply Chain *g* ($)
eb	Escalating factor for (regular production cost, backorder cost, and inventory cost) (%)
II(i,n,h)	Initial storage (units)
Ps(i,n,j)	Selling Price of product *n* produced at source *i* and distributed by endpoint *j* (100$/unit)
Mind(i,n)	Minimum acceptable quantity of product *n* to be distributed from source *i* in a period (units).
Maxd(i,n)	Maximum acceptable quantity of product *n* to be distributed from source *i* in a period (units).
Minp(i,n)	Minimum acceptable quantity of product *n* to be produced at source *i* in a period (units)
Maxp(i,n)	Maximum acceptable quantity of product *n* to be produced at source *i* in a period (units)
Prate(g)	Discount in the price for Supply Chain *g* (%)
Ed	Price elasticity of demand

Decision Variables:

Q(i,n,h)	Production of product *n* in the source *i* at time *h* (units)
W(i,n,h)	Inventor y level at source *i* of the product n at time *h* (units)
E(i,n,h)	Backorder of the source *i* of the product n at time *h* (units)
T(i,n,h,j)	Quantity delivered from the source *i* to endpoint *j* of product *n* at time *h* (units)

Binary variables:

X(i,n,h,j)	Binary variable identifying if product *n* is sent from source *i* to the endpoint *j* at time *h*
Y(i,n,h)	Binary variable identifying if the source *i* produces product *n* at time *h*

Objective functions:

z1(g)	total cost of SC *g* ($)
CST(g)	Spend of the buyers at each SC *g* ($)

APPENDIX A: Additional Case Study data and results

The proposed case-study, based on the different examples proposed by Wang and Liang (2004; 2005; and Liang, 2008),considers an initial inventory of 400 units of P1 and 200 P2 for both Plant 1 and Plant 3, and 300 P1 and 200 P2 for both Plant 2 and Plant 4.

To maintain the competence in the production/distribution/inventory tasks, the maximum and minimum production and distribution capacities are the same for all the plants (production min/max 0/10000 units of products in each time period, and distribution min/max 10/1200 units of products in each travel).

Table A.1. Payoff Matrix information, as function of the discount rates scenario.

Table A.2. Problem data.

Table A.3. Demand forecast.

Table A.4. Network distribution costs/delivery times.

Table A.5. Available labor levels ($F_{i,h}$).

Table A.6. Production capacities ($M_{i,h}$).

Table A.7. Payoff matrix for the competitive case (double demand).

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Table 1. Comparative results between SCs (standalone cases).

	SC1 Liang 2008	SC1 Original data	SC1 standalone	SC2 standalone
Obj. Funct.	min z1	min z1	min z1	min z1
z1($)	788 224	700 621	838 212	840 904
z2(hours)	2115	2300	1681	1747
Benefit ($)		3 803 378	3 665 787	3 663 095

Table 2. Optimal Distribution planning for SC1 and SC2.

SC1 (standalone)			Distr1	Distr2	Distr3	Distr4
Plant1	P1	March	0	820	500	1230
		April	0	2300	1200	3400
		May	0	4000	2400	5300
	P2	March	0	500	300	710
		April	0	720	400	1050
		May	0	2400	1150	3100
Plant2	P1	March	1000	0	0	0
		April	3000	0	0	0
		May	5000	0	0	0
	P2	March	650	0	0	0
		April	910	0	0	0
		May	3000	0	0	0

SC2 (standalone)			Distr1	Distr2	Distr3	Distr4
Plant3	P1	March	0	0	500	1230
		April	0	0	1200	3400
		May	0	0	2400	5300
	P2	March	0	0	300	710
		April	0	0	400	1050
		May	0	0	1150	3100
Plant4	P1	March	1000	820	0	0
		April	3000	2300	0	0
		May	5000	4000	0	0
	P2	March	650	500	0	0
		April	910	720	0	0
		May	3000	2400	0	0

Table 3. Comparative results between SCs (cooperative/competitive scenarios).

Table 3a: Comparative results (cooperative case)

	Coop. (original dmd)		Coop. (double dmd)	
	SC1	SC2	SC1	SC2
Obj. Funct.	min z1 (SC1+SC2)		min z1 (SC1+SC2)	
z1($)	515 516	286 997	1 051 348	592 487
z1total ($)	802 513		1 643 835	
z2(hours)	1 138		2295	
Benefit ($)	2 319 483	1 382 002	4 618 651	2 745 512
CST ($)	3 350 516	1 955 997	6 721 348	3 930 487

Table 3b: Comparative results (non-cooperative case)

Compet. (original dmd)		Compet. (double dmd)	
SC1	SC2	SC1	SC2
min CST (SC1)		min CST (SC1)	
702 559	100 734	1 274 981	370 421
803 293		1 645 402	
1117		2268	
3 148 722	544 265	5 750 339	1 598 178
4 553 841	745 734	8 300 302	2 339 021

Table 4. Payoff matrix for the competitive case (original demand).

SC1 discount ↓	SC2 disc →	0.00%		0.10%		0.20%		0.30%		0.40%	
		SC1	SC2	SC1	SC2	SC1	SC2	SC1	SC2	SC1	SC2
0%	z1($)	515,516	286,997	515,516	286,997	465,907	337,370	406,249	397,740	275,731	530,071
		802,513		802,513		803,277		803,989		805,801	
	z2(hours)	1,138		1,138		1,181		1,209		1,268	
	Benefit ($)	2,319,483	1,382,002	2,319,483	1,380,333	1,933,092	1,763,420	1,716,750	1,976,116	1,253,269	2,433,028
	CST($)	3,350,516	1,955,997	3,350,516	1,954,328	2,864,907	2,438,159	2,529,249	2,771,597	1,804,730	3,493,171
0.10%	z1($)	621,159	181,684	515,516	286,997	515,516	286,997	465,907	337,370	406,250	397,740
		802,843		802,513		802,513		803,277		803,989	
	z2(hours)	1,125		1,138		1,138		1,181		1,209	
	Benefit ($)	2,864,351	833,315	2,316,648	1,380,333	2,316,648	1,378,664	1,930,693	1,761,315	1,714,627	1,973,735
	CST($)	4,106,670	1,196,684	3,347,681	1,954,328	3,347,681	1,952,659	2,862,508	2,436,054	2,527,126	2,769,216
0.20%	z1($)	702,559	100,734	621,159	181,684	515,516	286,997	515,516	286,997	465,908	337,370
		803,293		802,843		802,513		802,513		803,277	
	z2(hours)	1,117		1,125		1,138		1,138		1,181	
	Benefit ($)	3,148,722	544,265	2,860,862	832,300	2,313,813	1,378,664	2,313,813	1,376,995	1,928,294	1,759,210
	CST($)	4,553,841	745,734	4,103,181	1,195,669	3,344,846	1,952,659	3,344,846	1,950,990	2,860,109	2,433,949
0.30%	z1($)	702,559	100,734	702,559	100,734	621,159	181,684	515,517	286,997	515,517	286,997
		803,293		803,293		802,843		802,513		802,513	
	z2(hours)	1,117		1,117		1,125		1,138		1,138	
	Benefit ($)	3,144,863	544,265	3,144,863	543,620	2,857,373	831,285	2,310,978	1,376,995	2,310,978	1,375,326
	CST($)	4,549,982	745,734	4,549,982	745,089	4,099,692	1,194,654	3,342,011	1,950,990	3,342,011	1,949,321
0.40%	z1($)	702,559	100,734	702,559	100,734	702,559	100,734	621,160	181,684	515,517	286,997
		803,293		803,293		803,293		802,843		802,513	
	z2(hours)	1,117		1,117		1,117		1,125		1,138	
	Benefit ($)	3,141,004	544,265	3,141,004	543,620	3,141,004	542,975	2,853,884	830,270	2,308,143	1,375,326
	CST($)	4,546,123	745,734	4,546,123	745,089	4,546,123	744,444	4,096,203	1,193,639	3,339,176	1,949,321

APPENDIX A

Table A.1. Payoff Matrix, as function of the discount rates scenario.

SC1/SC2	0.0%	0.2%	0.2%	0.3%	0.4%
0.0%	z1(A) z1(B) z2(A,B) Be(A,B) CST(A,B)	(A,B)	(A,B)	(A,B)	(A,B)
0.1%	(A,B)	(A,B)	(A,B)	(A,B)	(A,B)
0.2%	(A,B)	(A,B)	(A,B)	(A,B)	(A,B)
0.3%	(A,B)	(A,B)	(A,B)	(A,B)	(A,B)
0.4%	(A,B)	(A,B)	(A,B)	(A,B)	(A,B)

Table A.2. Problem data.

Source	Time	Product	a_{in}	c_{in}	d_{in}	l_{in}	r_{in}	vv_n
Plant1	3 months	P1	20	0.3	32	0.05	0.1	2
		P2	10	0.15	18	0.07	0.08	3
Plant2		P1	20	0.28	20	0.04	0.09	2
		P2	10	0.14	16	0.06	0.07	3
Plant3		P1	20	0.3	32	0.05	0.1	2
		P2	10	0.15	18	0.07	0.08	3
Plant4		P1	20	0.28	20	0.04	0.09	2
		P2	10	0.14	16	0.06	0.07	3

Table A.3. Demand forecast.

Demand	Distr1			Distr2			Distr3			Distr4		
Product	t1	t2	t3	t1	t2	t3	t1	t2	t3	t1	t2	t3
P1	1000	3000	5000	820	2300	4000	500	1200	2400	1230	3400	5300
P2	650	910	3000	500	720	2400	300	400	1150	710	1050	3100

Table A.4. Network distribution costs/delivery times.

Source	Product	Distribution Centers			
		Distr1	Distr2	Distr3	Distr4
Plant1	P1	[a]28/5.2[b]	10/1.8	42/13.5	22/2.8
	P2	25/5.2	9/1.8	40/13.5	20/2.8
Plant2	P1	12/2	15/2.5	50/15	35/6
	P2	11/2	14/2.5	45/15	32/6
Plant3	P1	44/9	59/12	11/4	35/6
	P2	39/9	54/12	10/4	32/6
Plant4	P1	15/3	10/2.0	38/14	41/7
	P2	13/3	9/2	35/14	37/7
Available space Rdd		19500	16000	10000	20000

[a] Delivery cost per truck to carry 100 dozen units.

[b] Delivery time.

Table A.5. Available labor levels ($F_{i,h}$).

	Time period		
	t1	t2	t3
Plant 1	965	1040	1130
Plant 2	850	920	990
Plant 3	965	1040	1130
Plant 4	850	920	990

Table A.6. Production capacities ($M_{i,h}$).

	Time period		
	t1	t2	t3
Plant 1	1550	1710	1870
Plant 2	1850	2050	2250
Plant 3	1550	1710	1870
Plant 4	1850	2050	2250

Table A.7. Payoff matrix for the competitive case (double demand).

SC1 discount ↓	SC2 disc →	0.00%		0.10%		0.20%		0.30%		0.40%	
		SC1	SC2	SC1	SC2	SC1	SC2	SC1	SC2	SC1	SC2
0%	z1($)	1,067,454	576,381	1,036,881	606,955	962,086	682,893	892,129	754,005	797,121	850,485
		1,643,835		1,643,836		1,644,979		1,646,134		1,647,606	
	z2(hours)	2,292		2,295		2,360		2,404		2,448	
	Benefit ($)	4,746,545	2,617,618	4,573,118	2,787,646	3,992,513	3,362,399	3,625,870	3,722,524	3,283,878	4,056,806
	CST($)	6,881,454	3,770,381	6,646,881	4,001,557	5,916,686	3,362,399	5,410,129	5,230,535	4,878,121	5,757,777
0.10%	z1($)	1,094,944	549,032	1,067,454	576,381	1,036,881	606,955	962,086	682,893	892,129	754,005
		1,643,976		1,643,835		1,643,836		1,644,979		1,646,134	
	z2(hours)	2,287		2,292		2,295		2,360		2,404	
	Benefit ($)	4,957,796	2,400,167	4,740,731	2,614,424	4,567,508	2,784,248	3,987,558	3,358,346	3,621,352	3,718,034
	CST($)	7,147,685	3,498,232	6,875,640	3,767,187	6,641,271	3,998,159	5,911,732	4,724,133	5,405,611	5,226,045
0.20%	z1($)	1,274,981	370,421	1,094,944	549,032	1,067,454	576,381	1,036,881	606,955	962,086	682,893
		1,645,402		1,643,976		1,643,835		1,643,836		1,644,979	
	z2(hours)	2,268		2,287		2,292		2,295		2,360	
	Benefit ($)	5,750,339	1,598,178	4,951,738	2,397,218	4,734,917	2,611,230	4,561,898	2,780,850	3,982,603	3,354,293
	CST($)	8,300,302	2,339,021	7,141,626	3,495,283	6,869,826	3,763,993	6,635,661	3,994,761	5,906,777	4,720,079
0.30%	z1($)	1,274,981	370,421	1,274,981	370,421	1,094,944	549,032	1,067,454	576,381	1,036,881	606,955
		1,645,402		1,645,402		1,643,976		1,643,835		1,643,836	
	z2(hours)	2,268		2,268		2,287		2,292		2,295	
	Benefit ($)	5,743,300	1,598,178	5,743,300	1,596,209	4,945,679	2,394,269	4,729,103	2,608,036	4,556,288	2,777,452
	CST($)	8,293,263	2,339,021	8,293,263	2,337,053	7,135,567	3,492,334	6,864,012	3,760,799	6,630,051	3,991,363
0.40%	z1($)	1,274,981	370,421	1,274,981	370,421	1,274,981	370,421	1,094,944	549,032	1,067,454	576,381
		1,645,402		1,645,402		1,645,402		1,643,976		1,643,835	
	z2(hours)	2,268		2,268		2,268		2,287		2,292	
	Benefit ($)	5,736,260	1,598,178	5,736,260	1,596,209	5,736,223	1,594,241	4,939,620	2,391,319	4,723,289	2,604,842
	CST($)	8,286,223	2,339,021	8,286,223	2,337,053	8,286,223	2,335,084	7,129,509	3,489,384	6,858,198	3,757,605

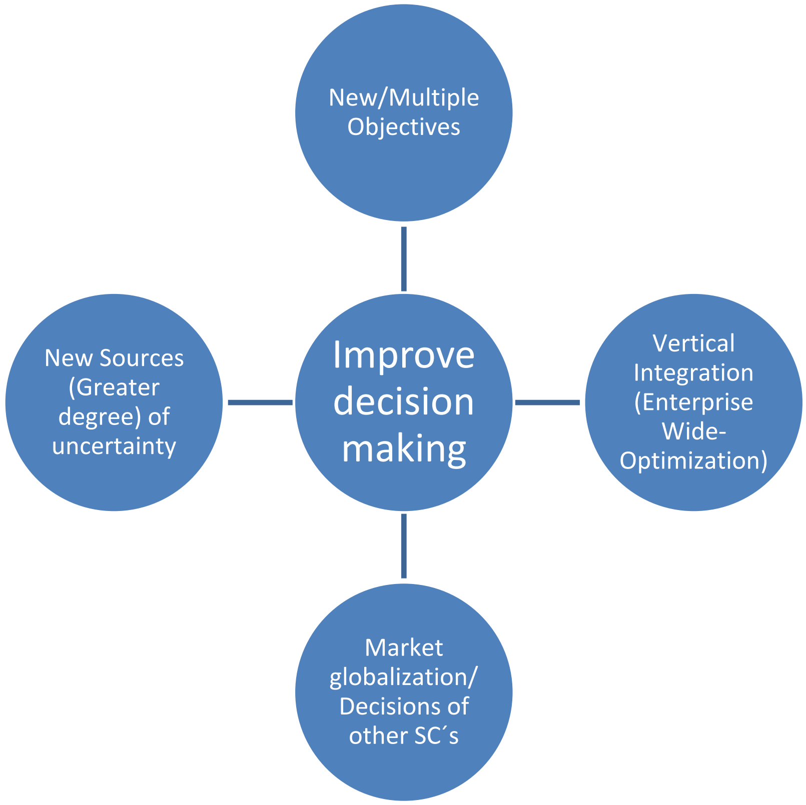

Figure 1. Open issues to improve Supply Chain decision making.

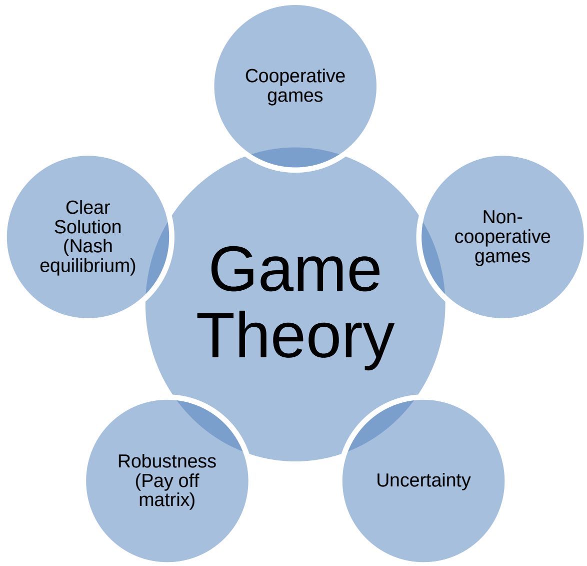

Figure 2. Use of the Game Theory as a tool to manage SC under uncertainty.

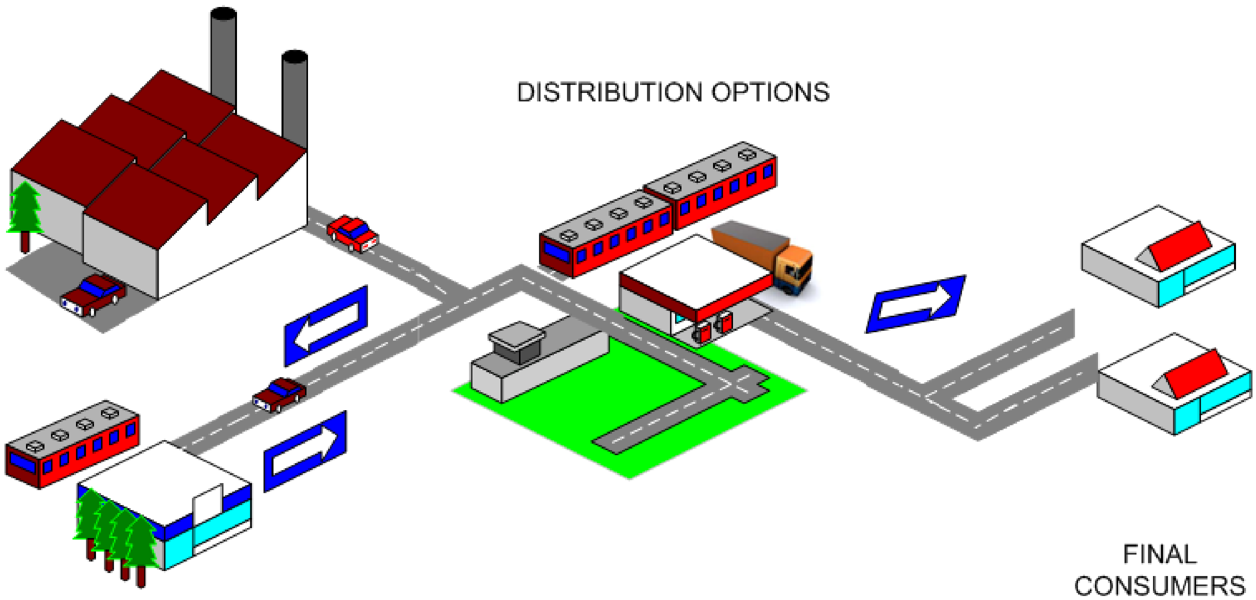

Figure 3. Typical SC Network configuration.

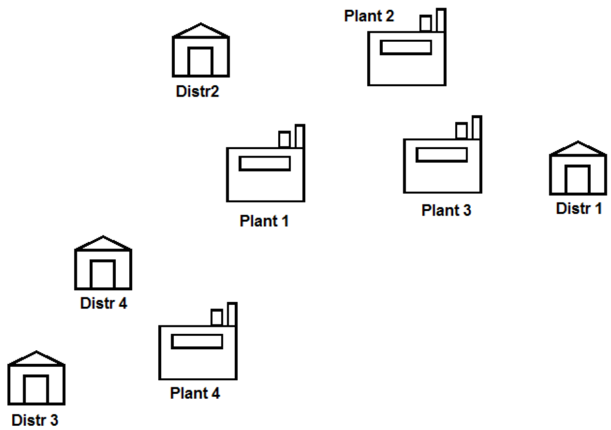

Figure 4. Description of the SC Network. Plants1-4 serve Distr1-4.

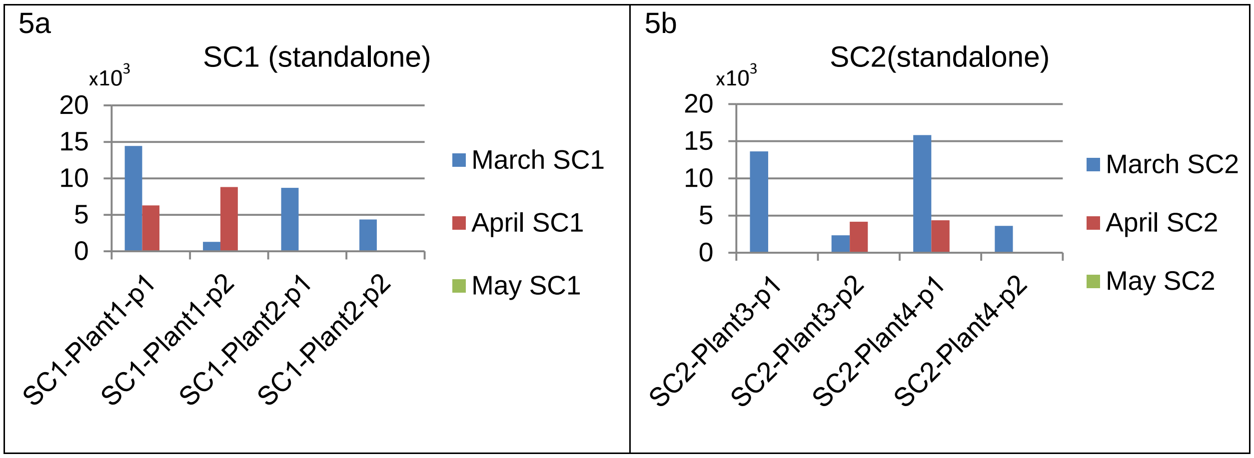

Figure 5. Optimal Production levels (Q_{inh}).

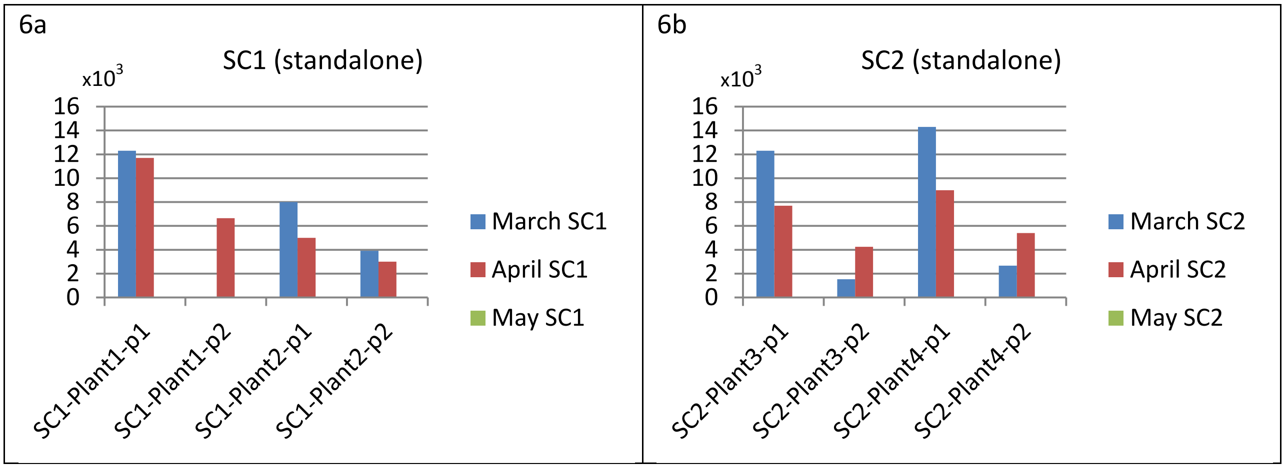

Figure 6. Optimal Inventory levels (W_{inh}).

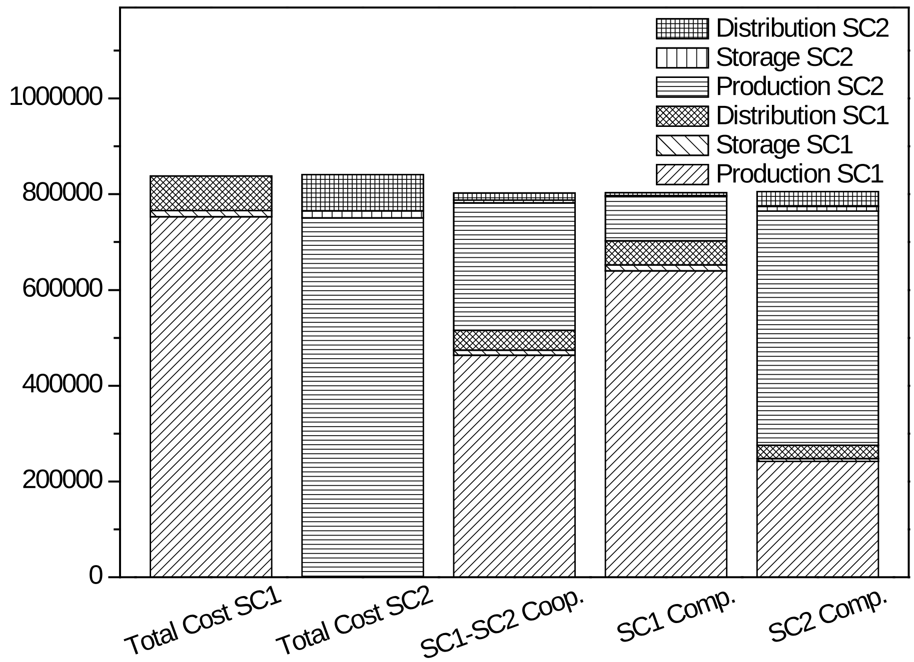

Figure 7. Cost Analysis for the studied examples