Towards Multi Enterprise-Wide Coordination for Large-Scale Chemical Supply Chains

Towards Multi Enterprise-Wide Coordination for Large-Scale Chemical Supply Chains

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I want to dedicate this thesis to the soul of my Mom in order to remind her that I am still watching over her dreams. But if she were alive, she would tell me that many people need this work more than her. Today, as my PhD journey comes to end, I thank Allah (God) for what He gifted me. Today, I realize how privileged I am, as I had the opportunity for which many people are longing, and others died while waiting. This makes me feel responsible for the dreams of those people. Today, I find myself obliged to dedicate the outcome of my hard work to those who are left behind the borders, to those who suffered and are still suffering from oppression, occupation, social injustice, marginalization, hunger, violence, dispossession and exploitation. I tell them I have reached this day because your suffering has inspired and motivated me, and was the fuel that led to this success. I know there are many people who are smarter than me, but unfortunately they could not have the opportunity to achieve what I did today. To them I say: never stop dreaming. The task will not be easy. You may face ignorance, injustice, unreasonable and arbitrary bosses, and people who will try to shut the voice of your dreams. I tell them: Never turn a face to those or listen. Without you, my work has no meaning. Keep on these three values: love, respect, and dignity.

Kefah Hjaila
Gaza, Palestine

Four things support the world: the learning of the wise, the justice of the great, the prayers of the good, and the valor of the brave

Prophet Muhammad (PBUH)

Summary

Most of the current Supply Chain (SC) decision support tools are devoted to the optimization of one objective function from a bias centralized perspective. However, due to the SC dynamics and the volatility of the market, chemical industry enterprises have to change the way to manage their SCs taking into consideration the coexistence with other interacting participants and their uncertain conditions, especially when they are surrounded with competitive third parties (i.e. raw materials and utilities suppliers, clients, waste and recovery systems, etc.).

Holding a large scale SC under the decision-making of one centralizing actor may not be feasible; collaborating with other enterprises may add mutual value to all participants. Such collaboration is hard to model, as each enterprise will really seek to optimize its individual revenues without complete information about the other enterprises decisions or their uncertain reaction, especially in a highly competitive and uncertain environment.

Towards multi-enterprise-wide coordination (M-EWC), the aim of this thesis is to contribute to the Process System Engineering (PSE) by new decision-support tools able to achieve global coordination/collaboration with all organizations participating in large-scale chemical SCs. Different approaches are proposed in this thesis to capture the interaction between the enterprises of contrasting/overlapping and competitive goals considering the role of the uncertainty of each participant on the decision-making of the other interacting participants and the decision-making of the whole system as well.

The first contribution of this thesis deals with the coordination with the supporting enterprises (third parties). A global coordination framework is developed to integrate the third parties decisions as full SC management problems in the decision-making process of a large-scale multi-product SC of multiple echelons. A generic coordinated tactical model is developed to highlight the interaction between the SC of interest and the third parties SC through the production vs. demand interaction between them. A comparison is undertaken between the proposed coordinated approach and the traditional non-coordinated approach to highlight the potential of the global coordination on the tactical decision-making and the resource consumption.

The second contribution of this thesis aims to highlight the potential of the third parties pricing decisions and their role to improve the efficiency of the SCM decision-making. To do so, the coordination framework proposed in the above mentioned paragraph is extended to integrate the third parties price policies in the decision-making of large-scale multi-echelon multi-product SCs. The third parties price policies are considered as degree of freedom decisions in the global coordinated SC tactical model. Integrating the competitive third parties price policies in the supply chain decision-making process as joint collaboration tools rather than fixed economic transactions results in effective coordination, so all participants can share responsibilities and future risks. Regardless of the additional complexity to the model formulations, integrating the price policies in the global coordinated decision-making process allows third parties to participate and compete as important partners, and thus they can flexibly control their financial channels.

Third, different approaches to approximate the third parties price policies variations are proposed and compared based on the average and discounting trends built on the demand elasticity theory. The consequences of using the different proposed pricing approximation models on the global coordination between the main enterprise and the third parties, regarding not only their effect on the tactical decision-making, but also the additional complexity in the mathematical formulations to be solved, are analyzed and compared. A comparison is undertaken between the discounting approximations and the traditional average approximation to highlight the effect of the selection of the pricing approximation on the tactical decision-making and the economic performance of the global coordinated system.

Fourth, the inter-organizational coordination/collaboration between different interacting enterprises is achieved based on cooperative and non-cooperative systems. The decisions obtained from the cooperative, non-cooperative, and standalone systems are analyzed and compared. Later, this thesis proves that non-cooperative systems lead to better coordination/collaboration with higher individual revenues, although the traditional cooperation hypothesis would lead to higher global revenues, in comparison with the standalone case.

Fifth, a novel non-cooperative non-zero-sum Scenario-Based Dynamic Negotiation (SBDN) approach, with non symmetrical roles, is proposed to set the best conditions for the coordination/collaboration contracts between enterprises of contrasting objectives participating as full SCs with their third parties in a large-scale multi-enterprise multi-product SC. Under the leadership of the manufacturer, the uncertain reaction of the follower partner resulted from the uncertain behavior of its SC third parties is considered in the leader model as a probability of acceptance. The proposed approach allows enough flexibility for the negotiating partners to accept or reject the collaboration, as their SCs can function as standalone systems, so the collaboration is not a must.

Sixth, an evaluation methodology is proposed to evaluate the negotiation outcome based on the probability distributions taking into consideration the variability of the follower profits successful scenarios.

The final contribution of this thesis lies in developing an integrated game theory approach for inter-organizational coordination. A non-cooperative non-zero-sum Stackelberg game is developed to capture the contrasting goals under different uncertain and competitive circumstances. The competition between the Stackelberg game players and the counterpart third parties is modeled through Nash Equilibrium game. Later in this document, a Stackelberg set of Pareto frontiers is obtained, where each point corresponds to a possible expected win-win coordination contract.

The comparison between the coordination/collaboration contracts resulted from this integrated game theory and the SBDN approache under the same circumstances shows how the coordination resulted from the integrated game theory approach leads to better solutions for the follower player, while the SBDN is a favorable approach for the leader player.

This thesis adds to the PSE different decision-support tools flexible and practical enough to optimize large-scale multi-enterprise SCs taking into consideration the decisions of all participants under different uncertain and competition circumstances. The proposed approaches in this thesis allow all possible links and business channels, which can be cope with future interactions.

Resumen

La mayoría de las herramientas de toma de decisiones para cadenas de suministro (CSs) químicas están dedicadas a la optimización de una función objetivo desde una perspectiva centralizada. Sin embargo, debido a la volatilidad del mercado, las empresas de la industria química tienen que cambiar la forma de gestionar sus CSs teniendo en cuenta la coexistencia con otros participantes, incluyendo las empresas externas "terceros" (es decir, proveedores de materias primas y de servicios públicos, clientes, sistemas de recuperación de residuos, etc.).

La gestión de una CS de gran escala bajo la toma de decisiones de un actor centralizado puede no ser realista. Colaborar con otras empresas puede incrementar los beneficios para todos los participantes. Esta colaboración es difícil de modelar, ya se trata de optimizar los ingresos individuales de cada empresa teniendo en cuenta la información detallada sobre el resto de ellas o su reacción incierta, especialmente en un entorno altamente competitivo e incierto.

Hacia la coordinación de múltiples empresas químicas a gran escala "Towards multi Enterprise-wide coordination (M-EWC)", el objetivo de esta tesis es contribuir al sistema de Ingeniería de Procesos "Process System Engineering (PSE)" mediante las nuevas herramientas de toma de decisiones capaces de lograr la coordinación /colaboración global entre todas las organizaciones que participan en las CSs. Diferentes enfoques son propuestos en esta tesis para capturar la interacción entre las empresas con objetivos contrastantes y competitivos teniendo en cuenta el papel de la incertidumbre de cada participante en la toma de decisiones del resto de participantes que interactúan, así como la toma de decisiones global del sistema.

La primera contribución de esta tesis se ocupa de la coordinación con los terceros. Una coordinación global está desarrollada para integrar las decisiones de los terceros en el proceso de toma de decisiones de una CS completa, de

gran escala, múltiples eslabones y varios productos. Se desarrolló un modelo táctico coordinado para resaltar las interacciones entre la CS bajo estudio y las CSs de los terceros a través de la interacción entre la producción y la demanda. Además se realizó una comparación entre el enfoque coordinado propuesto y el enfoque tradicional no coordinado para resaltar el potencial de la coordinación global en la toma de decisiones tácticas y el consumo de recursos.

La segunda contribución de esta tesis tiene como objetivo enfatizar el potencial de las decisiones de precio de los terceros y su impacto en la eficiencia de la gestión de la CS. Para ello, la coordinación global que se propone en el párrafo anterior se amplía para integrar las políticas de precio de terceros en la toma de decisiones de las CSs a gran escala. La política de precio de cada tercero se considera como un grado de libertad de decisión en el modelo táctico de la CS global y coordinada. La integración de las políticas de precios de los terceros competitivas en el proceso de toma de decisiones de la CS global, como herramientas de colaboración conjunta en lugar de transacciones económicas fijas, da como resultado una coordinación efectiva. Por lo tanto, todos los participantes pueden compartir responsabilidades y riesgos futuros. Independientemente de la complejidad adicional a la formulación del modelo matemático, la integración de las políticas de precios en el proceso de toma de decisiones de la CS global y coordinada permite a terceros participar y competir como socios importantes, y por lo tanto se pueden controlar de forma flexible sus canales financieros.

En tercer lugar, se proponen diferentes enfoques para aproximar las políticas del precio de los terceros y se comparan basados en las tendencias aproximadas (promedios) y descuentos de acuerdo a la teoría de la elasticidad de la demanda. Las consecuencias del uso de los diferentes modelos de aproximación de precio contemplados en la coordinación global entre la empresa principal y los terceros, no sólo con respecto a su efecto sobre la toma de decisiones tácticas, sino también la complejidad adicional en las formulaciones matemáticas que hay que resolver, son analizadas y comparadas. Se realizó la comparación entre las aproximaciones de descuento y la aproximación de promedio tradicional para resaltar el efecto de la selección de la aproximación de precios en la toma de decisiones tácticas y el rendimiento económico del sistema global coordinado.

Como cuarto punto, la coordinación/colaboración entre las diferentes organizaciones que interactúan se logra mediante sistemas cooperativos y no cooperativos. Las decisiones obtenidas de los sistemas cooperativos, no cooperativos y autónomos son analizadas y comparadas. En esta tesis se demuestra que los sistemas no cooperativos conducen a una mejor coordinación y colaboración con mayores ingresos individuales, aunque la hipótesis tradicional de cooperación da lugar a mayores ingresos globales en comparación con el caso autónomo.

En quinto lugar, se propone un nuevo método no cooperativo basado en escenarios de negociación dinámica "Scenario-Based Dynamic Negotiation (SBDN)" de no suma cero, con reglas no simétricas, para crear las mejores condiciones de contratos de coordinación/colaboración entre las empresas con objetivos contrastantes como unas CSs completas con sus terceros en una CS a gran escala, de múltiples empresas y con varios productos. Bajo la dirección del fabricante como líder, la reacción incierta del seguidor resultó del comportamiento incierto de sus terceros y es explícitamente considerado en el modelo del líder como una probabilidad de aceptación. El método propuesto presenta suficiente flexibilidad para que los negociadores acepten o rechacen la colaboración, ya que sus cadenas de suministro pueden funcionar como sistemas independientes, por lo que la colaboración no es obligatoria.

En sexto lugar, se propone una metodología para evaluar el resultado de la negociación basándose en la distribución de probabilidad, teniendo en cuenta la variabilidad de los beneficios del seguidor en escenarios exitosos.

La contribución final de esta tesis consiste en el desarrollo de un método integrado de la teoría de juegos para la coordinación entre organizaciones participantes en CSs químicas y globales. Un juego de Stackelberg no cooperativo de suma no cero se ha desarrollado para capturar los objetivos contrastantes bajo diferentes circunstancias de incertidumbre y competencias. La competencia entre los participantes del juego de Stackelberg y su contraparte (terceros) se modela aplicando el equilibrio de Nash. Más adelante en este documento, se obtiene un conjunto de fronteras de Pareto de Stackelberg, donde cada punto corresponde a un posible contrato de coordinación que garantiza ganancias (ganar-ganar).

La comparación entre los contratos de coordinación/colaboración resultó de esta teoría de juego integrada y la SBDN. Bajo las mismas circunstancias se muestra cómo la coordinación resultante de la teoría de juego integrada conduce a mejores soluciones para el seguidor, mientras que el SBDN es un enfoque favorable para el líder.

Esta tesis añade al PSE herramientas flexibles y prácticas de toma de decisiones para optimizar CSs de gran escala y multe empresas, teniendo en cuenta las decisiones de todos los participantes bajo diferentes circunstancias de incertidumbre y competencia. Las herramientas de toma de decisiones presentadas en esta tesis permiten modelar todas las conexiones y canales de negociación, por lo tanto dichas herramientas pueden ser ampliadas para considerar futuras interacciones con empresas adicionales (emergentes).

Acknowledgments

The work presented in this thesis document is part of what I have acquired during my research work. I would like to thank everyone who supports and encourages me till reaching this moment, especially my family, friends and colleagues. This thesis would not have been possible without your tremendous support.

I would never stop thanking my Mom for her last prayers asking God to lighten my way and to keep me safe. She left us before seeing this thesis becoming real. Today mother, I can find no enough words to express my gratitude to you for being the light when everything was gloom.

I do thank every single person in my family; my sisters: Tahrir, Soso and Dada; my brothers: Husni, Thaer, Gohod and Hamada; my nieces: Amwag (Moga), Ektemal (Lula), Rimas, Betol, Layan, Mira, Elin, Lin, Sila and Ektemal; my nephews: Amir, Gharib, Mahmoud (Dodo), Osama, Gaser, Osayd, Sohayb, Obada, and Fagr.

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Part I

Introduction

Chapter 1

Introduction

1.1 Preface

The chemical industry is one of the major components of the global market economy. Due to its hazardous nature and specific characteristics, it cannot be managed by the same rules as other sectors. Chemical industry provides goods and services for all economic sectors with €3.16 billion total sales, creating 1.20 million employments in 2014 (CEFIC, 2014). The world chemical sales are driven by China (33.2 %), US (16.7 %), and EU (16.7 %). During the last 20 years (Figure 1.1), EU lost the leading place in the chemical industry global market due to the rapid industrial expand in Asia, especially India and china.

Making the chemical industry more resource efficient is under the European Commission's economic targets by 2020. For example, according to CEFIC (2014), achieving 20% increase in the energy efficiency is on the top of these targets. The European Petrochemical Association (EPCA) jointly with CEFIC, in their technical report (McKinnon, 2004) suggest that effective management of the chemical industry through supply shain management (SCM) will enhance business competitiveness. Among the improvements that Process System Engineering (PSE) community stresses on are: effective allocation of resources (Shah, 2005); collaboration and coordination (McKinnon, 2004; Grossmann, 2005; Papageorgiou, 2009); incorporating financial decisions (Shapiro, 2006); and sustainability (Gao & You, 2015; Grossmann, Apap, Calfa, García-Herreros, & Zhang, 2016).

New decision-support tools are needed to make the chemical industry more resource efficient and more profitable, with less environmental impact and less

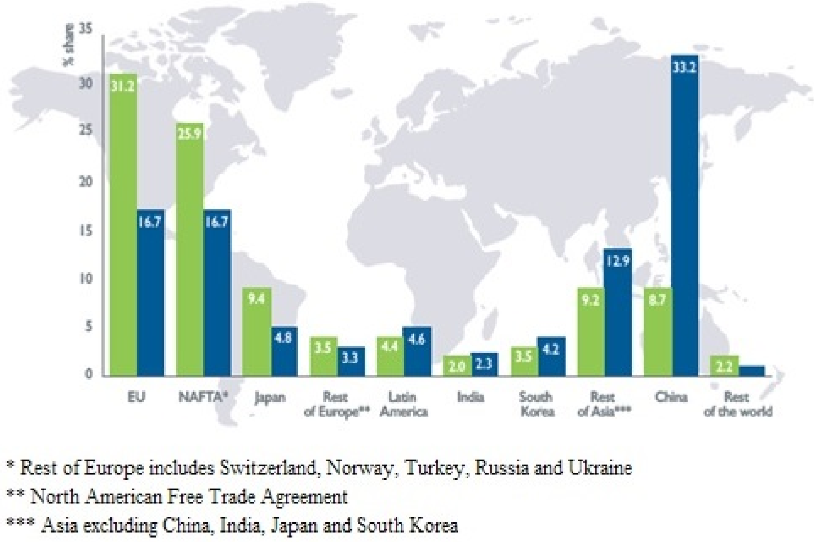


Figure 1.1: Chemical industry sales (CEFIC, 2014)

losses driven by uncertainty. This thesis focuses on the optimization of chemical industry large-scale multi-enterprise SCs through achieving the best coordination and collaboration conditions between their organizations, including the decisions of their third parties (i.e. raw materials and utilities suppliers, clients, waste and recovery systems, etc.).

1.2 Enterprise-wide optimization

The global market dynamics form a pressure on the chemical industry SCs enterprises to remain competitive. This makes the enterprise-wide optimization (EWO) one of the top concerns of the communities of Process System Engineering (PSE), Supply Chain Management (SCM), and Operational Research (OR) Figure (1.2). In order to enhance SC enterprise-wide revenues, EWO Decision-makers provide key tools based on chemical engineering knowledge from PSE; advanced modeling techniques from SCM; and theoretical concepts from OR.

EWO involves the optimization of R&D operations, the movements of resources through purchasing, manufacturing, storing, and distributing to the final customers at different investment terms (strategic, tactical, and operational). The main objectives of EWO is to respond to the final customers requirements with maximum enterprise-wide revenues, efficient facility utilization, minimum inventory, and minimum ecological footprint (Grossmann, 2012; Cardoso, Barbosa-Póvoa, & Relvas, 2016). This can be achieved through designing the SC at the strategic level, synchronizing the resources and economic

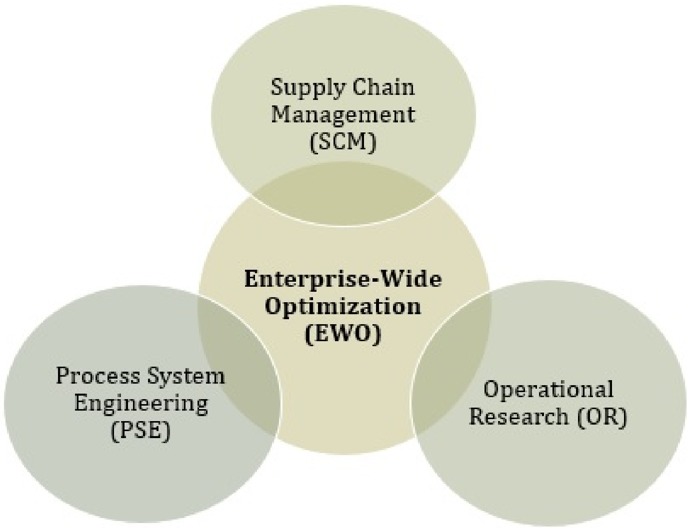


Figure 1.2: Enterprise-wide optimization (EWO)

flows under the objectives of the enterprise/s at the tactical level, and controlling the batch operations in order to fulfill part or all of the final customer requirements of goods and services (Figure 1.3).

PSE community has been pioneer in providing decision-support tools and solution algorithms to enhance EWO. The last conferences, mainly the joint event of PSE and the European Symposium on Computer Aided Process Engineering (ESCAPE)-PSE2015/ESCAPE25 in Copenhagen in May-June 2015; the 10^{th} European Congress of Chemical Engineering (ECCE10) in Nice in September-October 2015; and the American Institute of Chemical Engineers (AIChE2015) annual meeting in Salt Lake City in November 2015 had a high number of collaborations highlighting the goal of EWO. For more information, see `http://www.pse2015escape25.dk/`, `http://www.ecce2015.eu/`, and `http://www.aiche.org/conferences/aiche-annual-meeting/2015`. We also have participated in these conferences, amongst others, with different collaborations regarding multi-enterprise wide coordination (M-EWC).

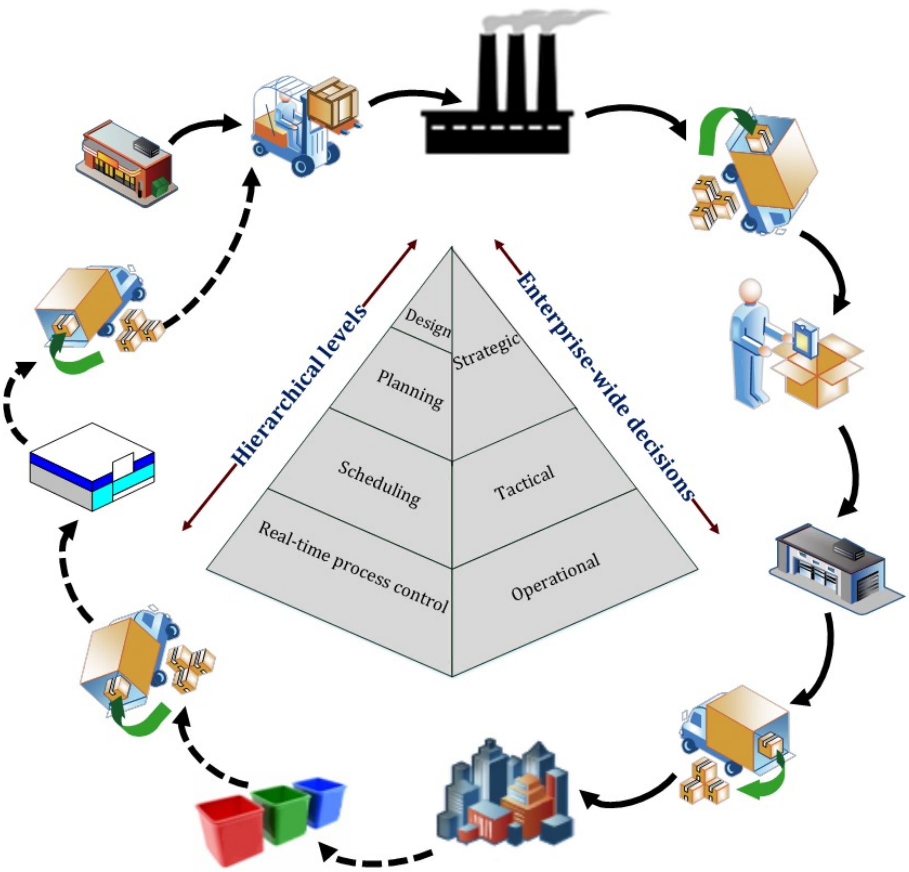


Figure 1.3: Enterprise-wide optimization main elements

1.3 Centralized and decentralized supply chains

A Supply chain (SC) is a network of facilities (i.e manufacturing sites, distribution centers/warehouses, collection centers, retailers, customers, etc.) distributed in different geographical locations and interconnected together with distribution links (Figure 1.4). The function of a SC is to produce products (intermediate/final) to be distributed later to customers.

A SC is qualified as centralized when the nodes of the SC structure, including the supporting enterprises facilities (i.e. raw materials and utilities suppliers, clients, waste and recovery systems, etc.) are controlled by a central enterprise stakeholder. Within centralized SCs decision-making, the whole decisions are synchronized under the goals of a central decision-maker. This biased situation neglects the roles of the interacting enterprises, including the third parties, in the decision-making process, leading to unfair decisions, which may result in the withdrawal of business partners from the system.

This thesis explores and extends this line by integrating the decisions of the interacting enterprises in the decision-making of the whole system of interest.

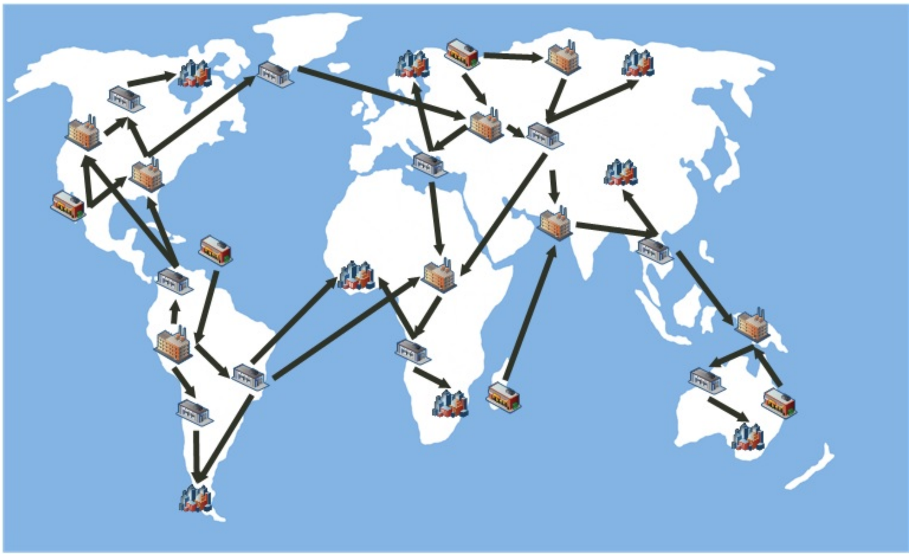


Figure 1.4: Supply chain network

A SC is decentralized when different enterprises participate as main decision-makers in the SC structure, with their own decisions in their own facilities, echelons, or full SCs (Figure 1.5). Decentralized decision-making influences the system-wide performance and the decision-making process (Vonderembse *et al.*, 2006). Within decentralized SCs, enterprises stakeholders pursue their individual objectives, which are possibly contrasting, regardless of the other partners objectives and uncertain reaction. Thus, additional complexity arises, as the whole decisions have to be synchronized under the different performance indicators of the different enterprises involved in the SC of interest.

The contrasting objectives mainly result on the value of the transfer price, which depends on the participants roles and the bargaining power of each player Gjerdrum, Shah, and Papageorgiou (2002); Zhang, Samsatli, Hawkes, Brett, Shah, and Papageorgiou (2013).

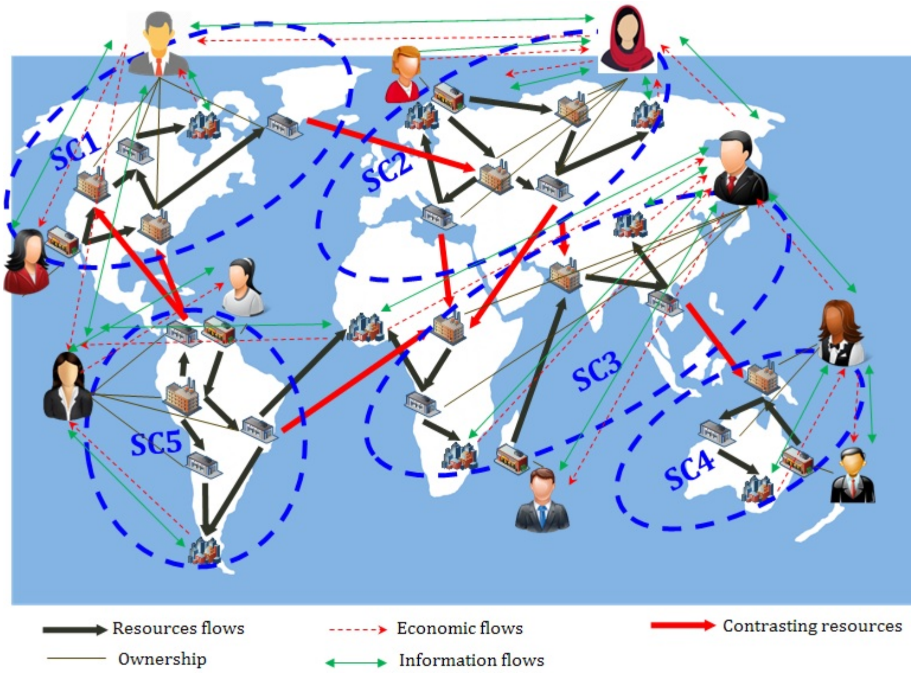


Figure 1.5: Decentralized supply chain network

Accordingly, this thesis extends the traditional definition of the SC from a set of facilities to a set of echelons/SCs and enterprises, in which effective multi-enterprise wide coordination (M-EWC) becomes a must, especially under uncertain and competitive circumstances.

1.4 Multi-enterprise wide coordination

Due to the globalization and market volatility, enterprises have to extend the scale of their SCs boundaries in order to cope with the new global market trends. Accordingly, enterprises have to change the way of managing their SCs towards "value preservation" in order to remain competitive and "value growth" in order to be more innovative (Grossmann, 2004). In order to enhance EWO, Varma, Reklaitis, Blau, and Pekny (2007) stress on the cross-functional coordination between the various layers of SCM decision-making (strategic, tactical, and operational).

In this current paradigm, as will be briefly discussed in chapter 2, current EWO optimization models implicitly focus on monopolistic situations from a centralized perspective, in which the decisions are imposed by one centralizing player. Holding a large scale SC for one decision-maker may not be realistic.

Thus collaborating with other enterprises may result in mutual benefits for all participants, so that all can stay competitive in the global market. Such collaboration is hard to model, as it depends on: i) the cooperative behavior of all participants, ii) uncertainty and risk propensity, and iii) the quality of the information that each partner acquires about the others.

In this thesis, the cross-functional coordination proposed by Varma *et al.* (2007) is extended to coordinate, at the same decision-making layer, the various enterprises involved in the system of study through defining a new term coined in this thesis as Multi-Enterprise Wide Coordination (M-EWC).

1.4.1 Global coordination

In order to stay competitive, chemical industry SCs have to integrate the decisions of the external supporting enterprises (i.e. raw materials and utilities suppliers, clients, waste and recovery systems, etc.) (called as third parties along this document). Global coordination with third parties is weakly dealt up today. Current Supply Chain (SC) tactical models focus on the material and information flows along few echelons of a SC without a clear vision about the third parties. The interaction with third parties is just represented by fixed parameters (unit price, capacity, etc.), usually regarded as a transaction process rather than a collaborative process. However, the decision-making is affected by the complex behavior of those third parties, especially if a detailed master plan is to be established. Accordingly, the detailed characteristics of the third parties must be integrated in the SC decision-making process as part of the whole system, and a global coordination is to be attained, so to avoid any unfair decisions.

Third parties must be given a degree of freedom through their price policies in the optimization process of the whole system of interest, so that they flexibly can control their financial channels and stay competitive. Since the third parties price policies are changing with time (i.e. electricity has different prices during the day), the decision support tools should be able to model/approximate the complex price policies of the third parties in order to guarantee mutual benefits for all participants.

1.4.2 Inter-organizational coordination

One of the major challenges facing M-EWC is integrating the financial marketing decisions with the operational decisions through inter-organizational coordination. Contrasting and competitive objectives appear between these two functional areas due to the tendency of the enterprises decision-makers to optimize their individual revenues without clear knowledge about the other interacting organizations or their uncertain reaction to the different decisions, and thus a additional complexity arises (see Figure 1.6).

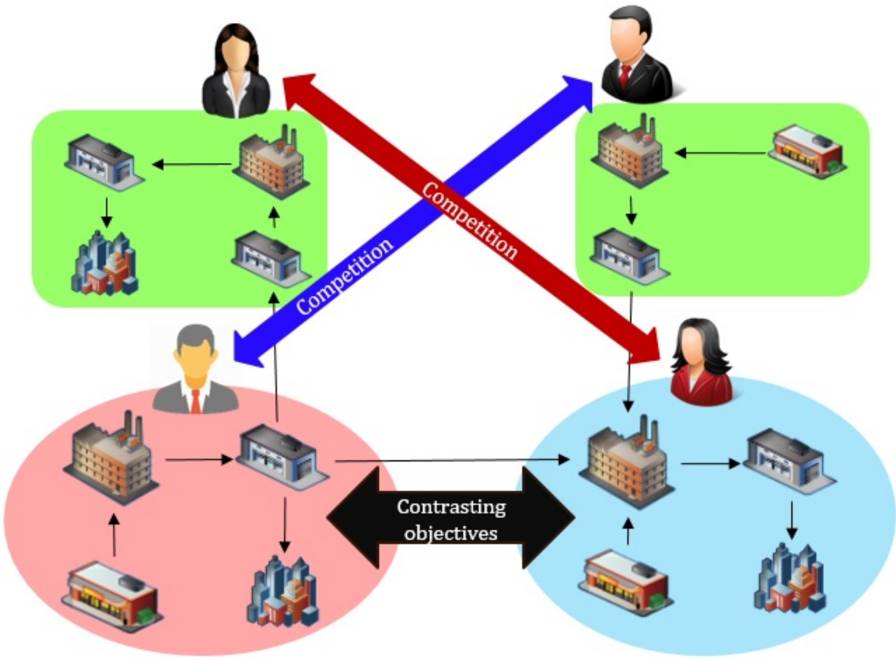


Figure 1.6: Enterprises contrasting and competing objectives

This thesis addresses this arising complexity through developing different coordination/collaboration approaches based on individual and global objectives, considering the detailed characteristics of all participants, including the third parties. Figure 1.7 summarizes the information needed to establish the coordination/collaboration.

Since the whole system performance is highly dependent on the collaboration actions of each participant (Perea-López, Grossmann, Ydstie, & Tahmassebi, 2001), the necessity to anticipate the other partners responses under different circumstances is a must. Multi enterprise-wide coordination should not be contemplated by itself since enterprises are facing dynamic market with high degree of uncertainty. Considering uncertainty explicitly helps in increasing the decisions robustness, and assures efficient capacity utilization (Papageorgiou, 2009). Evidently, considering uncertainty makes the decentralized decision-making process more complex, especially when synchronizing the activities of the multi-enterprise SC under the different objectives (contrasting/competitive) of different organizations. Accordingly, new decision support tools are needed to integrate different uncertain sources when constructing the coordination/collaboration models in order to reduce the risks and losses driven by uncertainty.

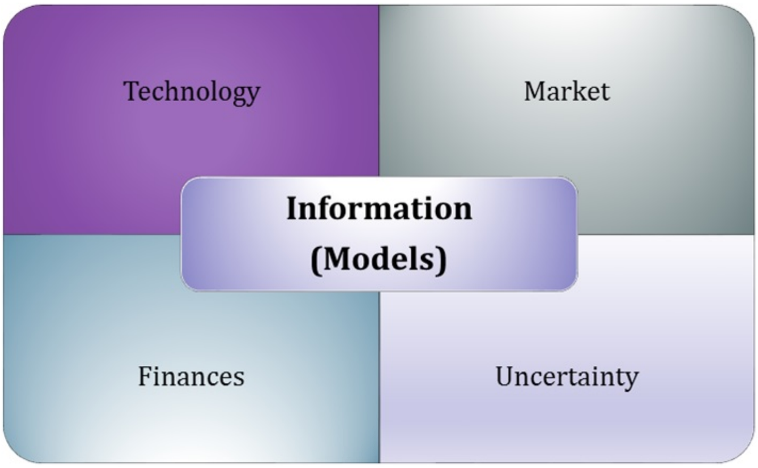


Figure 1.7: Coordination/collaboration information context

In this thesis, the proposed flexible coordination/collaboration approaches help enterprises decision-makers anticipating the other partners uncertain reactions to their decisions based on quantifying the probability of acceptance under different uncertain circumstances. Unlike the current PSE literature, the proposed coordination/collaboration approaches are flexible enough to help decision-makers in evaluating the coordination outcome based on their profits scenarios probabilities and risk behaviors under the different uncertain circumstances, including the uncertain nature of the third parties.

However, the trade-off between the payoffs of the different enterprises involved may lead to fundamental changes in the tactical decisions of the participating enterprises, in which is a challenge to be explored and analyzed. Such an analysis requires the consideration of the uncertain reaction associated with the different proposed coordination contracts, which results from their unknown decision process.

Chapter 2

State-of-the-Art

2.1 Introduction

Enterprise wide optimization (EWO) is one of the growing areas in PSE (Grossmann, 2005; Varma *et al.*, 2007; Wassick, 2009; Grossmann, 2012). This can be seen from the increasing number of publications in the last 20 years (Figure 2.1).

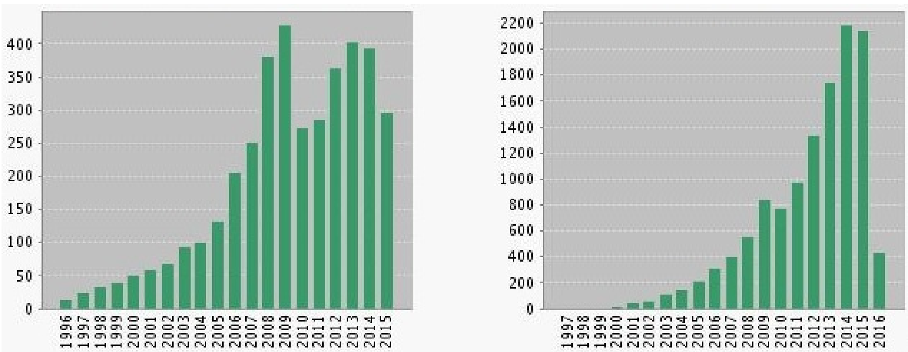


Figure 2.1: Articles published (left) under a topic of "enterprise optimization" and their citations (right) (Web of Science, 2016)

EWO involves in different sectors such as: chemicals production (Wassick, 2009; Velez & Maravelias, 2013), pharmaceutical industry (Sousa, Liu, Papageorgiou, & Shah, 2011; Susarla & Karimi, 2012; Ierapetritou, Muzzio, &

Reklaitis, 2016), shale gas (Cafaro & Grossmann, 2014; Elia, Li, & Floudas, 2015; Calderón, Guerra, Papageorgiou, Siirola, & Reklaitis, 2015), oil and gas production (Li, Ding, & Floudas, 2011; Gupta & Grossmann, 2012; Nikolaou, 2013), biofuel (Yue, You, & Snyder, 2014; Yeh, Whittaker, Realff, & Lee, 2015), petroleum (Neiro & Pinto, 2004; Rocha, Grossmann, & de Aragão, 2009; Fernandes, Relvas, & Barbosa-Póvoa, 2013; Tong, You, & Rong, 2014) (Figure 2.2).

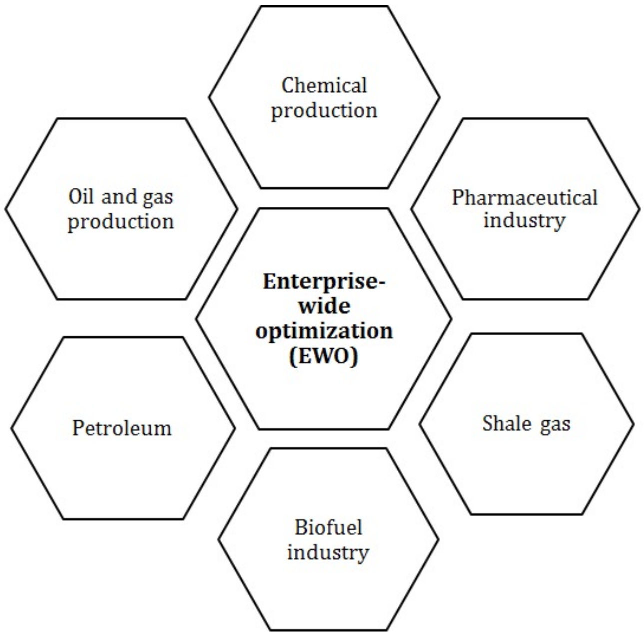


Figure 2.2: Enterprise-wide optimization (EWO) sectors

However, current literature works focus on optimizing chemical SCs from a centralized perspective. They disregard the coexistence with other participants, including the third parties, leading to unpractical decisions. This chapter includes a literature review of EWO through SC optimization from centralized and decentralized perspectives, followed by highlighting the main challenges and thesis objectives. The thesis outline can be found at the end of this chapter to describe the thesis document map.

2.2 Supply chain management(SCM)

The Council of Supply Chain Management (SCM) Professional (CSCMP, 2016) definition will be adopted here, as it copes with the context of this thesis: "Supply chain management encompasses the planning and management of all activities involved in sourcing and procurement, conversion, and all logistics management activities. Importantly, it also includes coordination and collaboration with channel partners, which can be suppliers, intermediaries, third party service providers, and customers. In essence, supply chain management integrates supply and demand management within and across companies ".

SC managers provide decisions at different hierarchical levels: strategic (design), tactical (planning), and operational (scheduling and process control).

2.2.1 Strategic (design) decision-making

SC design is an important component of EWO, as strategic decisions affect the value of the enterprise business. Efficient SC strategic decision-making affects the success of enterprises, especially, the large-scale ones. SC strategic (design) decision-makers provide long-term planning decisions (2-5 years), including configuring the SC network structure (internally and externally) in order to serve some or all of the customers' demands that cope with the enterprise/s goals. The basic information needed to build a design model are the fixed costs (investment, overhead, etc.) and variable costs (operating, manufacturing, distribution, taxes, etc.), market conditions, and availability of resources. Design models are usually solved under economic objective functions (annual profit, total capital cost, net present value (NPV), etc.).

The first long-term design model was the capacity expansion MILP of Sahinidis, Grossmann, Fornari, and Chathrathi (1989). Fernandes *et al.* (2013) propose a MILP model for the optimal design and retrofit of downstream petroleum multi-entity multi-product SC. The strategic decisions are the optimal depot locations, capacities, transportation modes and routes under the objective function of maximizing the total profit. The authors consider the different enterprises of the refineries, transportation, and inventory depots through a detailed cost structure based on shared margins and costs. The authors test their model on the Portuguese petroleum SC.

For water SC networks, Gao and You (2015) propose a mixed-integer linear fractional (MILFP) model for the optimal design and planning of freshwater supply network for shale-gas production. The strategic designs are on the selection of the freshwater sources, transportation modes, and water management options (disposal, wastewater treatment, on-site water treatment) under the objective function of maximizing the profit per unit freshwater consumption. The authors implement three solution algorithms to solve the MILFP model: parametric algorithm, reformulation-linearization method, Branch-and-Bound, and Charnes-Cooper transformation method.

Strategic decisions must account for uncertainty and risk measures in order to avoid any future disruptions. Ahmed and Sahinidis (2003) propose a multistage MILP stochastic capacity expansion model with fixed-charge expansion costs. Shen and Qi (2007) propose a MINLP stochastic design model for a distribution SC network under the uncertainty of demand. To solve the stochastic design model, the authors propose an embedded Lagrangian relaxation based solution algorithm in branch and bound. The Lagrangean relaxation subproblems are then solved through a low-order polynomial algorithm. Georgiadis, Tsiakis, Longinidis, and Sofioglou (2011) propose a MILP multi-product design model under time varying demand uncertainty. The authors captured the uncertainty in terms of a number of likely scenarios during the lifetime of the SC network. The resulting model is solved using standard branch-and-bound algorithms.

The definition of robust and resilient SCs in conjunction with stochastic programming allows solving SC design complex problems with high risk mitigation. Klibi and Marte (2012) propose a risk modeling approach for resilient SCs design and evaluation under uncertainty of demands, depots capacity, and ship-to-point processes. The authors analyze several stochastic programming models under several resilience formulations. Then they model the resilience disruptions, and evaluate the design decisions accordingly. Liu and Papageorgiou (2013) address the capacity planning and production of global SCs under different objectives: total cost, total flow time, and total lost sales. The authors solve the MOO using ϵ-constraint method and lexicographic minimax method considering the cost, responsiveness, and customer service level, simultaneously. García-Herreros, Wassick, and Grossmann (2014) propose a 2SSP design model for resilient SCs. The strategic decisions involve in selection of distribution centers, locations, storage capacities, and distribution flows at distribution centers nodes under the objective function of minimizing the sum of investment costs and expected distribution costs. The authors solve the large-scale model using multi-cut Benders decomposition algorithm.

Designing sustainable SCs has gained much attention due to environmental social concerns. Duque, Barbosa-Póvoa, and Novais (2010) integrate the environmental impact into an industrial SC design and planning MILP model. Eco-indicator 99 is selected as the environmental performance based on life cycle assessment (LCA). Minimizing the Eco-indicator 99 is considered as additional objective function besides the economic one. Their MOO model is solved using ϵ-constraint method and the Pareto-solution curve is obtained. Pinto-Varela, Barbosa-Póvoa, and Novais (2011) propose a MILP design and planning bi-objective model under the objective function of maximizing the annual profit and minimizing the Eco-indicator. Zeballos, Gomes, Barbosa-Povoa, and Novais (2012) propose a generic MILP closed-loop SC (CLSC) design and planning model under the uncertainty of quantity and quality of the return products. Their model is formulated as 2SSP and solved using scenarios under the objective function of profit maximization. You, Tao, Graziano, and Snyder (2012) propose a multi-objective MILP design model for cellulosic ethanol SCs under economic, environmental, and social objectives. The economic objective is to minimize the total annualized cost; the environmental objective is to minimize greenhouse gas emissions; and the social objective is to maximize the number of created local jobs. The MOO model is solved using ϵ-constraint method and the Pareto-solutions is obtained. The decisions obtained are the optimal SC configuration, facility selection, equipment technology, production planning, inventory, and logistics levels. Cardoso, Barbosa-Póvoa, and Relvas (2013) propose a MILP design and planning CLSC model considering, simultaneously, the production, distribution and reverse logistics. The uncertainty of products demands is tackled through scenario-tree approach towards maximizing the expected NPV. The design decisions are on capacity and location of facilities (production plants, warehouses, and retailers), processes technology, inventory, forward and reverse flows amounts. Kalaitzidou, Longinidis, and Georgiadis (2015) propose a generalized multi-period MILP model for the optimal design of multi-product CLSC. Their model is solved using standard branch-and-bound algorithm to find the optimal design and planning decisions that satisfy markets demands with minimum overall capital and operational cost.

For designing flexible SCs, Kalaitzidou, Longinidis, Tsiakis, and Georgiadis (2014) propose a flexible design model considering generalized production and warehousing nodes. Their proposed model considers that production/warehousing nodes can receive material from any supplier or any other generalized production/warehousing node, and deliver resources to markets or any other production/warehousing node. The model is optimized to find out the optimal SC structure that satisfies the market demands with minimum overall capital and operational cost.

Challenges in strategic decision-making

Strategic decision-making has been widely studied. However, the following issues need further research:

- Designing global decentralized SCs considering all possible connections and nodes.
- designing/redesigning inventory systems for multi-echelon SCs under different sources of uncertainty (i.e. lead time, unit prices, inventory cost, etc.)
- Modeling and solving complex multi-stage multi-scale stochastic design large-scale SCs.
- Coordinating between the different scales of multi-layer SCs under uncertainty.
- Solving the nonlinearities of any of the objective functions when dealing with MOO.
- Integrating design and control decisions, including safety measures.
- Implementing to real industry SCs.

2.2.2 Tactical (planning) decision-making

Tactical or medium-term planning involve in providing a master plan regarding the allocation of activities to capacities. This includes the optimal resources acquisition, manufacturing production, storage, and distribution levels that satisfy (or not) the market demands of the final products over a time horizon up to several months.

Tactical optimization models are constructed based on material and energy balances at the SC nodes with known data such as market demands, distances between entities, unit costs, chemical processes recipes, capacities (raw material supply, production, storage), etc. Typical tactical models are solved under the objective function of maximizing revenues or minimizing costs. However, many objective functions can be analyzed through multi objectives or multi-criteria optimizations. The mathematical formulations of the tactical problems may results in LP, MILP, or MINLP programs. Discrete variables arise from incorporating financial issues such as discrete cost functions, price fluctuations, price policies, etc. Nonlinearities arise from the chemical processes recipes, cost functions, etc.

Tactical decision-making has been studied so far in the PSE literature. Wilkinson, Cortier, Shah, and Pantelides (1996) propose a tactical model for the optimal production and distribution of a continent-wide industrial SC (3 factories, 14 markets warehouses, over 100 products). Their model gives each factory flexibility to store in any warehouse and to deliver products to any market. McDonald and Karimi (1997) develop a multi-period LP tactical model for the optimal sourcing and production of multi-product multi-site real SC. Their model formulation takes into account additional constraints such as single sourcing, internal sourcing, and transportation times.

Based on time-indexed formulation, Timpe and Kallrath (2000) propose a multi-period multi-site MILP tactical model to optimize the production and distribution levels at different time scales. For more complex problems, Jackson and Grossmann (2003) develop a multi-period NLP tactical model for the production and distribution of multi-product multi-site SC (4 sites, 118 products, 5 markets). The main feature of their model is considering non-linear process recipes for each production plant. To reduce the computational times, the authors propose two solution techniques based on Lagrangean decomposition, spatial decomposition and temporal decomposition. According to the context of their paper, the temporal decomposition provides optimal solutions in less computational time comparing with the spatial decomposition. Neiro and Pinto (2004) proposed a multi-period MINLP planning model to optimize the stream flow rates, qualities, operational variables, inventory and entities assignment of a petroleum SC. The SC under study (59 exploration sites, 11 refineries, five terminals, 20 types of supply petroleum, 32 products) includes different process units, storage tanks, terminals and pipelines, which are interconnected by intermediate streams. The processing units are modeled based on the framework proposed by Pinto and Moro (2000). Schulz, Diaz, and Bandoni

(2005) address a large-scale problem through multi-period MILP and MINLP tactical models for a petrochemical pipeline SC. The objective function of their proposed model is to maximize total profit considering discontinuous product delivery and penalties for not meeting markets demands and inventory targets.

solving large-scale tactical models is one of the big challenges of PSE. For pharmaceutical large-scale SCs, Sousa *et al.* (2011) optimize the tactical decisions of a pharmaceutical SC from the production stages at primary and secondary sites to products distribution to customers. To solve the large-scale model, the authors propose two decomposition algorithms. The first algorithm is based on decomposing the SC into independent primary and secondary sub-problems and solving each one separately. The second algorithm is using temporal decomposition by separating the main problem into several independent sub-problems, one per each time period. Susarla and Karimi (2012) develop a global MILP tactical model for multi-period multi-product multi-national pharmaceutical SC (34 entities producing 9 different products). Their model accounts for the optimal procurement, production, and distribution levels taking into consideration the international tax differentials, after-tax profit, storage costs, material shelf-lives and waste treatment/disposal.

For food industry large-scale SCs, van Elzakker, Zondervan, Raikar, Hoogland, and Grossmann (2014a) address the tactical optimization of fast moving consumer goods industry (i.e. ice-cream, yoghurt, etc.). They develop tactical MILP model taking into consideration shelf-life restrictions in order to prevent unnecessary waste and missed sales. To do so, they analyze and compare three methods: i) tracking the age of products directly, ii) forcing inventory at the end of products shelf-life, iii) using the hybrid method (a combination of the last two methods). According to the context of the problem they analyze, the first method is computationally inefficient, although it provides optimal solutions. The second method leads to less optimal solutions, but in less computational time. The hybrid method leads to near optimal solutions with reduction in the computational time of factor 5 when compared with the first method. Later on, the authors van Elzakker, Zondervan, Raikar, Hoogland, and Grossmann (2014b) propose a decomposition algorithm based on single stock keeping sub-models in order to reduce the computational time of the same problem with high number of stock-keeping units. Slack variables are introduced into the capacity constraints of their model in order to represent the interaction between the stock-keeping units.

Due to the volatility of markets, tactical management under uncertainty is one of the spot topics of PSE literature. Amaro and Barbosa-Póvoa (2009) propose a multi-period LP tactical model for the optimization of the RM supply, production, storage, and distribution levels of CLSCs under the uncertainty of demands and retail price. They solve the resulting model using a standard Branch and Bound (B&B) method. Verderame and Floudas (2009) propose a multi-site tactical with production disaggregation model to calculate the production and shipment profile for the multi-product large-scale SC network under the uncertainty of demand. the authors tackle uncertainty through the robust optimization approach extended from Lin, Janak, and Floudas (2004). You, Pinto, Grossmann, and Megan (2011b) address the inventory-distribution tactical management under uncertainty for industrial gas SCs. To tackle the uncertainty of demand and loss or addition of customers, a multi-period multi-stage stochastic MINLP model is proposed to determine the optimal deliveries, replenishments, and inventories. To solve the non-convex MINLP stochastic model, the authors develop a tailored branch-and-refine algorithm based on successive piecewise-linear approximation. A clustering-based heuristic approach is proposed to solve the routing model. Niknejad and Petrovic (2016) address the reverse logistics within inventory-production planning framework under uncertainty. The authors analyze two alternative recovery routes including re-manufacturing and disposal routes. The uncertainty of demand and return quantities of products of different quality levels are modeled using fuzzy trapezoidal numbers. A two phase fuzzy MILP algorithm is developed to optimize the inventory and production planning of the network under study.

For logistics management, Dondo, Méndez, and Cerdá (2011) integrate the vehicle routing with cross-docking and time windows in the tactical model of hybrid multi-echelon multi-item distribution networks. The main goal of their MILP tactical model is to satisfy the markets demands at minimum transportation cost. The authors solve the mathematical model using a branch-and-cut algorithm. Kopanos, Puigjaner, and Georgiadis (2012) develop a production-logistics tactical model for a real-life multi-site food SC using different alternative transport modes for delivering the final products. The main feature of their model is considering products families instead of products. Changeovers are considered in their model formulation and optimized. Dondo and Méndez (2016) develop a tactical model to optimize the forward and backward flows and logistics of a SC network. Their coordinate the vehicles tours in order to assure efficient forward and backwards flows. To reduce the computational times, the authors present a column-generation based decomposition algorithm.

Challenges in tactical decision-making

The above-described works focus on the SC echelons based on single flow information biased by a centralizing decision-maker. They disregard the detailed characteristics of the resources flows from/to other interacting enterprises and third parties. Such information is not sufficient to cope with the new competitive market trends resulting in the collaboration with other partners and the incorporation of their decisions, including third parties. Furthermore, the impact of each interacting enterprise on the other enterprises decision-making through efficient coordination is weakly dealt up to now, especially for large-scale SCs, when a detailed master plan is to be established. From this point, many issues need further research:

- Coordinating multi-enterprise decentralized SCs considering the decisions of all participates, including third parties.

- Integrating financial issues such as third parties price policies in the tactical decision-making.
- Considering detailed representation of resources and echelons.
- Analyzing the competition among enterprises from a decentralized perspective.
- Considering the uncertain reaction of any participating enterprise on the other enterprises decisions.
- Analyzing the impact of the uncertain behavior of third parties on the global SC decision-making.
- Modeling the contrasting objectives between the enterprises of different interests.
- Integrating planning-scheduling levels with detailed description of the production process and capacity allocation.
- Incorporating new sources of uncertainty and developing/combining new solution techniques.
- Developing sustainable tactical models with new environmental metrics.

2.2.3 Operational (scheduling) decision-making

Scheduling (lot sizing or sequencing) decision making involves in allocating equipment and production resources over a short time period to manufacture a set of products to be delivered to the SC and then to the customer. Operational decision-makers provide answers to how, when, and where questions at the unit process scale. "How to produce" refers to resources requirements (energy, product, etc.); "when to produce" refers to the sequencing of tasks (start and end times of each task); and "where to produce" corresponds to the assignment of tasks to process units. A scheduling model aims to minimize the operating costs, makespan (total length of the schedule), or to maximize the profit for a time period up to days based on known data such as demand and supply.

Scheduling problems can be divided into offline and online problems. Offline scheduling is based on available data about current and future situations. Whereas, online scheduling is based on available past and current data without complete information about the future events.

Operational (scheduling) decision-making has been studied so far. Kondili, Pantelides, and Sargent (1993) propose the first State Task Network (STN) mathematical formulation to represent the batch processes. The STN is built on unit-to-task allocation and equal time discretization. Binary variables are used to allocate tasks to units at each scheduling time period resulting in MILP model. The main features of their model is that tasks, feedstock, intermediate and final products (states) are represented as the network nodes.

Shah, Pantelides, and Sargent (1993) modifies the (Kondili *et al.*, 1993) model including relaxation improvements to reduce the computational times. Pantelides (1994) develop an alternative representation for the scheduling problem as Resource Task Network (RTN). Schilling and Pantelides (1996) propose a scheduling MILP model with continuous time representation based on the RTN proposed by Pantelides (1994). To reduce the computational times, they develop a branch-and-bound algorithm considering both continuous and discrete variables. Mockus and Reklaitis (1999) extend the continuous-time scheduling to consider nonlinearities for batch and continuous processes.

Later on, many significant research works have been carried out to improve the operational decision-making. Bok, Grossmann, and Park (2000) propose a multi-period scheduling model for continuous process networks. To reduce the computational times, a bi-level decomposition algorithm is used by relaxing the original large problem into small relaxed problems. Sanmartí, Puigjaner, Holczinger, and Friedler (2002) develop a novel S-graph representation to solve complex recipes processes with less computational times. The nodes of the S-graph represent the production tasks, whiled the arcs represent the correlations among tasks. Maravelias and Grossmann (2003) propose a new continuous-time MILP scheduling model based on STN for multipurpose batch plants. Their modeling approach accounts for tasks constraints, variable batch sizes and processing times, storage policies, batch mixing/splitting, and sequence-dependent changeover times. For multi-stage batches, Prasad and Maravelias (2008) develop a MILP scheduling model for the optimal selection of batches, assignment of batches to units, and sequencing of batches under the objective functions: minimizing the makespan, lateness and production cost, and maximizing the profit.

For single-stage batch plants, Castro, Erdirik-Dogan, and Grossmann (2008) develop a short-term scheduling model for single-stage batch plants with sequence-dependent changeovers and the number of used batches. Their modeling approach allows a single task to be processed in all batches. According to the context of their work, their proposed approach leads to better performance than the traditional RTN with less computational times. Later on, Castro and Grossmann (2012) solve the short-term scheduling of single-stage batch plants with different units and different tasks. Three time representations are compared for their model: i) immediate precedence, ii) general precedence, and iii) multiple-time grids. They find out that multiple-time grids representation leads to better performance with less computational times. Liang and Hui (2016) propose a MILP scheduling model to minimize the makespan of single-stage multi-product batch production with sequence-dependent changeovers. Subtour elimination methodology is proposed to reduce the computational times.

For pharmaceutical applications, Maravelias and Grossmann (2004) propose a scheduling MILP optimization model for the tasks testing of new products development. The main features of their model is that it allows the installation of new resources during the testing course as decision variables in function of the handling cost and duration of the test.

For bio-energy processes, Dunnett, Adjiman, and Shah (2007) propose a scheduling model for biomass-to-heat batch plants. They adapt the STN approach to represent the biomass harvesting, densification, drying, storage and transportation activities.

Scheduling under uncertainty is one of the main issues under research, Subramanian, Maravelias, and Rawlings (2012) develop a MILP re-scheduling model within state-space framework, in which scheduling disturbances are modeled. Their proposed approach is based on single-solution. The authors deal with the scheduling as on-line deterministic problem, in which the model is optimized based on current data and forecasts to obtain a single solution. When new data becomes available, they re-optimize (re-schedule) the model to determine another single solution. Zhang, Cremer, Grossmann, Sundaramoorthy, and Pinto (2016a) develop a MILP scheduling model for power continuous industrial processes providing interruptible load. To tackle the uncertainty of demand, the authors proposed an adjustable robust optimization approach considering recourse decisions in the form of linear decision rules.

For sustainable scheduling, Zhou, Cheng, and Hua (2000) address the multi-objective scheduling integrating environmental issues for petrochemical industrial processes. A goal programming (GP) model is developed based on the analytic hierarchy process to evaluate the priorities of the objectives and to weight the deviation variables. Yue and You (2013) develop a multi-product multi-purpose scheduling model using the bi-criterion optimization method under economic and environmental objectives. Maximizing the productivity is considered as the economic objective,whereas minimizing the environmental impact is considered as the environmental objective. The bi-objective model is solved using ϵ-constraint method. Their approach results in a mixed-integer linear fractional program (MILFP), which is solved using a reformulation-linearization method and Dinkelbach's algorithm. For closed-loop scheduling, Cafaro and Cerdá (2014) present a MILP continuous-time scheduling model considering the reverse flows of multi-products pipelines transferring oil products in both directions. The model calculates the precise time instants for the oil flow reversals to provide input and output schedules in one step.

Challenges in operational decision-making

Scheduling problems have been solved widely with a focus on single site problems. However, few studies consider multi-site scheduling problems due to the high computational times arising from the additional complexity. Many issues are still at the beginning such as:

- Scheduling multi-site problems with dynamic and differential equations.
- Incorporating financial issues such as prices adjustments over time.
- Sustainable scheduling with detailed production process description.
- Considering synthesis in hybrid systems.

- Scheduling under new sources of uncertainty (i.e capacities).
- Re-scheduling when changes occur in the decentralized SC network.
- Developing/modifying solution algorithms to reduce the computational times of non-linear scheduling models of complex recipes.
- Modeling real-time scheduling under uncertainty considering the lead time variability from batch to batch.
- Developing new evolutionary meta-heuristics to solve feasibility problems.
- Integrating scheduling and design complex models under uncertainty.

2.3 Integrated supply chain management

Efficient SC operation ideally requires the integration of different decisions at different SCM hierarchical layers (Grossmann, 2004; Shah, 2005; Varma *et al.*, 2007; Maravelias & Sung, 2009; Papageorgiou, 2009). The necessity to integrate different decisions associated to different time and economic scales is one of the complex topics in PSE.

Many works have been carried out to integrate the decision-making of the SCM hierarchical levels. A good state-of-the-art can be found in Maravelias and Sung (2009), who review the main integration challenges and propose two main approaches for the production planning and scheduling integration:

i) including the scheduling decision variables directly in the tactical models. However, although this approach would lead to optimal solutions, the size of the problem is increased leading to additional complexity. Many works have been carried out to solve large-scale integrated problems through developing advanced solution strategies. For example, Erdirik-Dogan and Grossmann (2007) develop a bi-level decomposition technique based on rolling horizon for the optimization of integrated planning-scheduling problem of a single plant multi-product batch reactors with sequence-dependent changeovers. They anticipate the changeovers in the batch problem using sequencing constraints for more accurate predictions. Later on, Terrazas-Moreno, Trotter, and Grossmann (2011) extend this work to multi-site multi-period SCs. To reduce the computational time, they develop a new hybrid method combining bi-level with spatial Lagrangean decomposition.

ii) approximating the scheduling decisions by relaxing all or part of the scheduling constraints, or aggregating some of the decision variables. Sung and Maravelias (2007) include a convex approximation of the scheduling decisions as a set of linear surrogate constraints into the planning model. The scheduling model is solved off-line to obtain the convex approximation of the production levels, and the total production cost is estimated in function of the production.

Neiro and Pinto (2004) integrates the planning and scheduling decisions for a complex real petroleum SC of refineries, terminals, and pipelines networks as multi-period large-scale MINLP problem. They integrate the processing units model of Pinto, Joly, and Moro (2000) into the tactical model formulation. The decisions obtained are the stream flow rates, properties, operational variables, inventory and entities assignment. Kopanos, Puigjaner, and Maravelias (2011) propose a MILP planning-scheduling model integrating the discrete-time planning grid with the continuous-time scheduling. They consider sequence-dependent switchover times and costs for product families, and sequence-independent switchover for products belonging to the same family. At the planning level, the product orders are handled at intermediate due-dates considering holding and backlog costs. At the scheduling level, the equipment unit constraints, switchover times and costs, maintenance activities, and idle production periods are considered.

Shin and Lee (2016) propose a planning-scheduling model to optimize the RM procurement system from multiple suppliers by a manufacturer under uncertainty. They formulate the planning problem as a Markov decision process (MDP) incorporating demand and supply uncertainties. Their integrated model is decomposed into subproblems: the planning problem for ordering RMs, and the scheduling problem for unloading the orders. The authors integrate the inventory dynamics at the planning level with the detailed unloading schedule at the scheduling level in order to compute the state-transition and the cost of MDP formulation. Their integrated model is solved using dynamic programing method. To reduce the computational times, linear approximation and heuristics-based estimation of cost and state transition are used for this problem. Zhao, Ierapetritou, and Rong (2016) propose a MINLP planning-scheduling model for a real-world ethylene plant. The planning model incorporates the operating variables and energy utilization in both the thermal cracking and the down-stream process.

For the scheduling and control integration, Chu and You (2012) propose an integration approach to solve the scheduling and the control problems, simultaneously. The model formulation contains discrete variables from the scheduling problem and constraints from the control problem. Their approach results in a non-convex mixed-integer nonlinear fractional model, which is solved using Dinkelbach's algorithm. The model is implemented and solved on-line to four case studies of polymer manufacturing networks with different products numbers.

For the design and scheduling integration, Kallrath (2002) integrate scheduling and strategic planning in a MILP multi-period model for multi-site real production SCs. For simultaneous planning, scheduling and control, Gutiérrez-Limón, Flores-Tlacuahuac, and Grossmann (2016) propose a mixed integer dynamic model for the optimal planning, scheduling and control of continuous reactors. A heuristic strategy is developed as a reactive approach to tackle the uncertainty of demand. The heuristic strategy is based on re-scheduling of the products to be manufactured after the disturbance.

For the design and planning integration, Kallrath (2002) propose a simultaneous design and planning model for multi-site SCs. Their integration model aims to optimize the equipment selection, RM acquisition, production levels under the objective function of maximizing the net profit. Tsiakis and Papageorgiou (2008) develop a MILP design-planning model for a multi-echelon multi-product multi-site SC with outsourcing possibilities under operational and financial constraints. The operational constraints include efficiency, production and supply and material balance constraints. The financial constraints include the import duties, plant utilization, exchange rates and plant maintenance. You and Grossmann (2008) propose a MINLP design-planning model of multi-product SC taking into consideration the capacity expansion under the objective functions to maximize the NPV and to minimize the expected lead time (as a measure of responsiveness). Their problem is formulated as bi-criterion optimization model and solved using the ϵ-constraint method. The Pareto-solutions curve is obtained to represent the trade-off between the economic criteria and the SC responsiveness. They integrate the stock-out probability with the demand uncertainty in order to predict the stock levels. The model is optimized over the selection of manufacturing sites and distribution centers, process technology, production and inventory levels.

Later on, You, Grossmann, and Wassick (2011a) propose a multi-period MILP design-planning model for the optimal capacity, production and distribution for the multi-site multi-product Dow chemical manufacturing SC. The authors consider capacity modification and reactor modifications (due to changing product type) in the model formulation. They solve the large-scale model and compare the results using Lagrangean decomposition and bi-level decomposition algorithms. According to the context of their approach, the bi-level decomposition is more efficient in terms of computational times and optimality gaps.

Considering SCM integration for closed-loop SCs (CLSC), Lee, Gen, and Rhee (2009) develop a design-planning model for reverse-logistics SCs to optimize the re-manufacturing processes, technology design, and disassembly strategies. They solve the logistics problem using a priority-bases genetic algorithm approach (priGA) with encoding method. Zhang, Shang, and Li (2011) develop a design-planning model for the reverse logistics of a municipal solid wastes SC. Their model aims to optimize the re-manufacturing, storage, and distribution activities under uncertainty. To solve the large-scale model, the authors propose a piecewise interval programming. Salema, Barbosa-Povoa, and Novais (2010) propose a design-planning MILP model for a country size glass industry SC to optimize the SC structure, RM supply, manufacturing, storage, and distribution levels. Later on, Zeballos *et al.* (2012) extend the work of Salema *et al.* (2010) by considering the uncertainty of the reverse flows (quantity and quality). Cardoso *et al.* (2013) develop an integrated design-planning model to optimize the reverse logistics, facilities location, reprocessing, and capacity expansion of a CLSC under uncertainty of demand. Zeballos, Méndez, Barbosa-Povoa, and Novais (2014) develop a multi-period multi-stage design-planning model for the optimization of CLSCs considering the emissions costs of the different logistic modes. The model is formulated as multi-stage stochastic program to tackle the uncertainty of supply and demand under the objective function of minimizing the total expected cost minus the expected revenues. In order to reduce the computational time of the problem, the authors apply scenario reduction algorithms to generate a representative subset of scenarios.

Challenges in integrated supply chain management

Although the integration leads to effective SCM decision-making, it yields large-scale and complex optimization problems. The necessity to solve the arising complexity from integrating the different decisions at different time and economic scales is one of the challenging topics. Many issues need more research such as:

- Integrating SCM hierarchical levels for large scale multi-period problems.
- Integrating SCM decision-making for decentralized SCs, including efficient hierarchical coordination.
- Incorporating different business functionalities and financial issues at different decision levels.
- Considering logistics and inventory management.
- Developing/modifying algorithms to solve stochastic integration models.
- Combining different techniques to manage uncertainty.
- Designing a plant or a reactor simultaneously with the scheduling/planning.
- Considering new sustainability measures, risk, and resilience.

Table 2.1 summarizes the aforementioned literature works that tackle the strategic, tactical, operational, and integrated supply chain management.

Table 2.1: Supply chain management literature

Authors	Design	Retrofit	Planning	Scheduling	Multi-objective	Uncertainty	risk	Sustainability
Ahmed and Sahinidis (2003)	✓	✓				✓		
Amaro and Barbosa-Póvoa (2009)			✓			✓		
Bok *et al.* (2000)				✓				
Bonfill *et al.* (2008)				✓		✓		
Cafaro and Cerdá (2014)				✓				
Cardoso *et al.* (2013)	✓		✓		✓	✓		✓
Castro *et al.* (2008)				✓				
Chu and You (2012)				✓				
Dondo *et al.* (2011)			✓					
Dondo and Méndez (2016)			✓					
Dunnett *et al.* (2007)				✓				
Duque *et al.* (2010)	✓		✓		✓	✓		✓
van Elzakker *et al.* (2014a)			✓					
van Elzakker *et al.* (2014b)			✓					
Erdirik-Dogan and Grossmann (2007)			✓	✓				
Fernandes *et al.* (2013)	✓	✓	✓					
Gao and You (2015)	✓		✓		✓			✓
García-Herreros *et al.* (2014)	✓	✓	✓			✓	✓	
Georgiadis *et al.* (2011)	✓					✓		
Jackson and Grossmann (2003)			✓					
Kalaitzidou *et al.* (2014)	✓							
Kalaitzidou *et al.* (2015)	✓							
Kallrath (2002)	✓			✓				
Klibi and Marte (2012)	✓	✓				✓✓		
Kondili *et al.* (1993)				✓				
Kopanos *et al.* (2011)			✓	✓				
Kopanos *et al.* (2012)			✓					
Lee *et al.* (2009)	✓		✓					
Liang and Hui (2016)				✓				
Gutiérrez-Limón *et al.* (2016)			✓	✓		✓		
Liu and Papageorgiou (2013)	✓		✓		✓			✓
Liu and Papageorgiou (2013)	✓		✓		✓			✓
Maravelias and Grossmann (2003)				✓				
Maravelias and Grossmann (2004)				✓				

Continued on next page

Table 2.1– continued from previous page

Authors	Design	Retrofit	Planning	Scheduling	Multi-objective	Uncertainty	risk	Sustainability
Maravelias and Sung (2009)			✓	✓				
McDonald and Karimi (1997)			✓					
Mockus and Reklaitis (1999)				✓				
Neiro and Pinto (2004)			✓					
Niknejad and Petrovic (2016)			✓			✓		
Pantelides (1994)				✓				
Pinto-Varela *et al.* (2011)	✓		✓		✓			✓
Prasad and Maravelias (2008)				✓	✓			✓
Sahinidis *et al.* (1989)	✓		✓					
Salema *et al.* (2010)	✓		✓					✓
Sanmartí *et al.* (2002)				✓				
Schilling and Pantelides (1996)				✓				
Schulz *et al.* (2005)			✓					
Shah *et al.* (1993)				✓				
Shen and Qi (2007)	✓					✓		
Shin and Lee (2016)			✓			✓		
Sousa *et al.* (2011)			✓					
Subramanian *et al.* (2012)				✓		✓		
Sung and Maravelias (2007)			✓	✓				
Susarla and Karimi (2012)			✓					
Terrazas-Moreno *et al.* (2011)			✓	✓				
Timpe and Kallrath (2000)			✓					
Tsiakis and Papageorgiou (2008)	✓		✓					
Verderame and Floudas (2009)			✓			✓		
Wilkinson *et al.* (1996)			✓					
You and Grossmann (2008)	✓		✓	✓	✓	✓		✓
You *et al.* (2012)	✓		✓		✓			✓
You *et al.* (2011a)	✓	✓	✓					
You *et al.* (2011b)			✓			✓		
Yue and You (2013)				✓	✓			✓
Zeballos *et al.* (2012)	✓		✓		✓	✓		✓
Zeballos *et al.* (2014)	✓		✓		✓	✓		✓
Zhang *et al.* (2011)	✓		✓			✓		
Zhang *et al.* (2016a)				✓				
Zhao *et al.* (2016)			✓	✓				
Zhou *et al.* (2000)				✓	✓			✓

2.4 Financial management

Current SCM decision support tools provide decisions based on the chemical process operations knowledge rather than the marketing decisions. However, incorporating financial issues in the decision-making process is necessary to enhance business functionality and the corporate value of the enterprise.

A few works address the financial performance in the decision-making process. For example, Longinidis and Georgiadis (2013) integrate the financial performance and credit solvency within the SC design process under economic uncertainty. A multi-objective MINLP model is developed including the financial as economic added value and credit solvency through a valid credit scoring formulations.

Prices as dynamic marketing variables affect the products demands, so any decision related to pricing will affect the whole system decision-making. In the traditional economic literature, decisions related to prices were taken by marketing managers (Dorward, 1987). One of the early studies to incorporate the price theory with the SC decisions is Whitin (1955), who analyzes the coordination between the price theory and the inventory control based on the lot-size and price dependent demand for a news-vendor problem. Later on, Federgruen and Heching (1999) optimize the pricing and the inventory replenishment strategies under the uncertainty of demand. Their model formulation considers that the prices can be adjusted over time in function of the amounts ordered and the initial stock at the first time period. The order-up-to-level is considered as a base-stock level with an optimal price policy each time period. If the stored amounts are less than the base-stock level, a discount price is offered in function of the initial stock. Chen and Simchi-Levi (2004) coordinate between the pricing, ordering, and inventory decisions for single-product SC under demand uncertainty. They consider a fixed and variable ordering cost in function of the ordered amounts. The main objective is to obtain the best pricing strategy and inventory policy that maximize the expected profit of the SC. Their model is similar to the model proposed by Federgruen and Heching (1999), but the last do not consider a fixed cost for the quantity ordered. Later on, Rodriguez and Vecchetti (2012) propose a scenario-based mid-term planning model considering the sales contracts at different price levels under different demand scenarios.

Price promotion based on discounting is one of the important elements of the product trade. Price elasticity of demand as a discounting strategy has first been used by Weng (1995) to determine the retail price for a single buyer SC. Later on, Kallrath (2002) presents a nonlinear pricing correlation between the RM purchase and unit price within an integrated design-operational framework. Shapiro (2004) extends the SC optimization models to include revenue functions based on price elasticity of demand. Xiangtong, Bard, and Yu (2004) develop a SC planning model for a single supplier-retailer SC under uncertainty of demand. The authors analyze the deviation of the SC cost under different demand disruptions scenarios using price discount policies based on price elasticity of demand theory. Wang (2005) extends the typical quantity discounts by incorporating the markets annual volume for a two-echelon SC. Hsieh, Liu, and Wang (2010) propose a short-term discounting model based on price elasticity of demand for one distributor-multiple retailers SC. In their model, the distributor offers different price discounts for the retailers considering a linear price-demand function and constant elasticity demand. Liu, Shah, and Papageorgiou (2012) propose a MILP planning model for multi-product SC considering products price fluctuation based on price elasticity of demand. Hashem, Baboli, and Sazvar (2013) develop a MINLP multi-period planning model for multi-product multi-site production SC considering retail price discounts.

Considering individual objectives, Viswanathan and Wang (2003) propose a quantity discount methodology based on price elasticity of demand for a single-vendor single-retailer SC considering individual revenues. Unlike Weng (1995), the authors implement a Stackelberg game to determine the equilibrium point between the vendor and the retailer. Iida (2012) studies the effect of the production cost reduction on the decentralized SC of one production plant and multiple suppliers. Wang, Huang, and Wei (2015) address the relationship between a manufacturer and a retailer based on price discounts. The optimization models are solved in a decentralized way to obtain the optimal order quantity and selling price for the retailer, and the optimal wholesale price and lot size for the manufacturer. Then the model is solved as a joint centralized model to find the optimal order quantity, the selling price, and the lot size.

Challenges in financial management

However, the reviewed literature regards the interactions with other enterprises, including third parties as economic transactions represented by fixed parameters (capacity, price, etc.). Understanding the third parties policies is crucial for effective enterprises coordination and business development. None of the reviewed literature integrates the price policy of third parties as part of the decision-making process. By doing so, much information is lost leading to sub-optimal decisions, which may affect the global SC equilibrium, especially in a competitive uncertain environment.

Enterprises decision makers not only have to focus on their financial interests, but also on the dynamic interaction with other interacting/supporting participants and their uncertain behaviors. However, none of the reviewed literature addresses the uncertain behavior of other participants resulted from the uncertainty of price policy from a decentralized perspective. Many challenges arise from these gaps, such as:

- Integrating financial cash flows with the SC process operations.
- Controlling the enterprise cash flow and enhancing the corporate value (Shapiro, 2004).
- Quantifying probability of acceptance,robustness, and financial risk.

- Incorporating pricing decisions with the inventory and control decisions.
- Integrating financial issues of the other participants, including third parties policies.
- Investigating pricing approximations methods.
- Incorporating the uncertainty of price polices in the decentralized SC decision-making.
- Analyzing the impact of the decisions related to pricing on the SC activities and performance.
- Developing/modifying decomposition techniques to reduce the computational time resulting from incorporating the financial decisions of other participants.

2.5 Coordination/collaboration management

Enterprises decision-makers in chemical industry seek value preservation in order to remain competitive and value growth in order to become more innovative (Grossmann, 2004). However, due to globalization, SC dynamics, and market volatility, chemical industry SCs enterprises have to change the way of managing their SCs in order to remain competitive and innovative.

Many decision-support tools have been proposed to help enterprises in optimizing their SCs, especially at the tactical level, which is the focus of this thesis. Most of these works, as briefly discussed in the above-sections (2.2, 2.3, 2.4) are devoted to optimize the overall objective of the whole system from a centralized perspective. However, managing a large scale SC by one centralizing decision-maker may not be feasible. Thus, collaborating with other enterprises may add value to all participants, so that all can remain competitive in the global dynamic market. Such collaboration is hard to model, as it depends on the cooperative behavior of all participants, which is also affected by the uncertain nature of their third parties. Each participant enterprise will really seek to optimize its individual revenues (possibly contrasting) without considering the risks associated with the uncertain reaction of others, and thus complexity arises.

A few works at the bargaining literature have been carried out to solve the arising complexity through negotiations built on cooperative and non-cooperative approaches. Cooperative approaches such as: cost-sharing (Meca, Timmer, Garcia-Jurado, & Borm, 2004), backorder cost-sharing (Hennet & Arda, 2008), risk-sharing (Inderfurth & Clemens, 2014), revenue-sharing (Cao, Wan, & Lai, 2013; Govindan & Popiuc, 2014; Heese & Kemahlioglu-Ziya, 2016), multi-agent systems (Moyaux, Chaib-draa, & D'Amours, 2006; Cao, Feng, & Ma, 2007; Banaszewski, Arruda, Simão, Tacla, Barbosa-Póvoa, & Relvas, 2013;

Yuan, Xu, Zhang, & Rong, 2013; Singh, Chu, & You, 2014). Non-cooperative approaches such as: rebates and return contracts (Taylor & Xiao, 2009), quantity flexibility contracts (Lian & Deshmuck, 2009), Shortage penalty (Li, Li, & Cai, 2013), option-contracts (Li, Ritchken, & Wang, 2009; Zhao, Wang, Cheng, Yang, & Huang, 2010; Zhao, Ma, Xie, & Cheng, 2013; Yi & Guo, 2015), buy-bak contracts (Zhao, Choi, Cheng, Sethi, & Wand, 2014), compensation contracts (He, 2015), game theory (Li *et al.*, 2009; Xiong, Zhou, Li, Chan, & Z., 2013; Huang, Song, Lee, & Ching, 2013; Yue & Fengqi, 2014).

For cooperative approaches, the participating enterprises decision-makers agree on forming a coalition towards a common objective function. Meca *et al.* (2004) use a cooperative cost-sharing approach to optimize the tactical decisions of a decentralized inventory SC. They consider a collective of enterprises cooperating to minimize the joint inventory cost based on cost sharing. Hennet and Arda (2008) propose a cooperative model for a producer-supplier SC based on sharing the backorder costs and capacity reservation in order to maintain resources flows. Based on risk-sharing, Inderfurth and Clemens (2014) propose a price coordination contact for a buyer-supplier newsvendor SC with a stochastic demand. Their cooperative framework is based on sharing the risks between the actors. Assuming that both actors are exposed to risks of over-production or under-delivery. As a result, they find out that sharing the risk affects the buyers orders and the suppliers production decisions. Yi and Guo (2015) propose a put-option coordination contract between a risk-neutral manufacturer and a risk-averse retailer in a two echelon simple SC.

A trading method based on revenue-sharing has been also suggested as a cooperative methodology. Cao *et al.* (2013) propose a revenue-sharing approach to capture the competence between different retailers competing on a limited production of one manufacturer under uncertainty of production and final demands. The relationship between the manufacturer and competing retailers is modeled as a Stackelberg game under the leading role of the manufacturer. According to their framework, the manufacturer provides the initial production plan based on her/his uncertain conditions regardless of the uncertain reaction of the retailers, which may lead to SC disruptions. Furthermore, the retailers are obliged to buy from one manufacturer giving them a narrow space of options to negotiate or reject. Later on, Govindan and Popiuc (2014) propose an analytical model for the coordination of two-echelon reverse flow decentralized SC based on a revenue-sharing contract. In their model, they consider that the retailer has to make a discount for the customer as a motivation to return the used products (as incentives). Heese and Kemahlioglu-Ziya (2016) propose a revenue-sharing coordination contract for a single supplier-retailer SC. Their analytical model is based on enhancing the information flows between the partners through paying incentives to the retailer for preparing sales reports.

Multi-agent systems (Moyaux *et al.*, 2006) emulate the cooperative negotiations among different interacting enterprises (agents). In this line, Cao *et al.* (2007) propose a Pinch Multi-Agent Genetic Algorithm (PMAGA) model to optimize the tactical decisions of a water network SC with various participants. In their approach, all participating enterprises (agents) cooperate to minimize the total use of freshwater. Banaszewski *et al.* (2013) develop a multi-agent auction-protocol tactical model for the optimal planning of a Brazilian oil SC. The participating agents representing the entities of the SC cooperate to optimize the oil products transport plan (types, amounts, allocation) under the objective function of minimizing the total cost of the whole SC. Bid values and the sequence of auction commitments are also identified in their approach. Yuan *et al.* (2013) propose a multi-agent stochastic model based on global convex constraints. In their model, the participating agents cooperate to maximize the summation of their objective profits. Singh *et al.* (2014) develop an agent-based model to solve the competition between different bio-fineries as corn markets considering different corn purchase prices among biofineries. The agent-based is implemented to simulate the corn markets. The dynamic corn purchase prices are obtained using a double-auction process by the biofineries agents, farmer agents, and a food market agent. After obtaining the corn purchase prices, the MINLP design model of the main biofinery SC is optimized under the objective function of maximizing the NPV.

However, multi-agent-based systems are based on cooperative situations, in which all participants cooperate towards a common goal. This approach disregards the individual objectives of all participants and their uncertain behavior, which may lead to sub-optimal decision-making of the whole system.

Non-cooperative negotiations are used when the participating enterprises seek to optimize their individual objectives. Many works have been carried out to set coordination contracts between the negotiating players. Based on rebate and return contracts, Taylor and Xiao (2009) address and compare the coordination for a manufacturer-retailer SC based on two different contracts: rebate and return contracts. For rebate contracts, the supplier agrees on paying incentives to the retailer for the quantities sold to customers above an agreed threshold. For the return contract, the manufacturer agrees on paying compensations to the retailer for unsold amounts. They analyze both coordination contracts under the uncertainty of the customer demand. According to the context of their approach, the coordination based on rebate contracts leads to better solutions than the return-contracts. Zhao *et al.* (2010) propose an option-contract cooperative approach for a supplier-retailer SC based on coordinating the manufacturer production capacity with the retailer reserved quantities.

Lian and Deshmuck (2009) propose a quantity flexibility contract between a supplier and a retailer. In their approach, the retailer receives discounts in case of purchasing in advance. Li *et al.* (2013) propose a coordination contract agreement based on shortage penalty for a very simplified SC structure of one seller and one buyer (no external markets). Such a method gives high dominance to the buyer partner, as the seller is obliged to collaborate. Zhao *et al.* (2013) propose a negotiation method based on bi-directional contracts (call/put options) for a manufacturer-retailer SC network. For the call option, the manufacturer has to buy a specific amount of products at a specific price for reserving the production capacity, while for the put option, the retailer must pay an allowance for canceling or returning an order.

Xiong *et al.* (2013) propose an analytical model to coordinate between a virgin RM supplier and a non-integrated manufacturer within a decentralized closed-loop SC based on non-cooperative game using a backward induction. Based on buy-back contracts, Zhao *et al.* (2014) coordinate between a supplier and a retailer participating in a two-echelon SC under demand uncertainty. The retailer assigns a price per unit quantity purchased from the supplier with the condition to return a specific amount at the end of the sales season. Based on compensation contracts, He (2015) proposes a coordination framework based on complete and partial compensation contracts a decentralized reverse channel re-manufacturer-supplier SC. The acquisition pricing and manufacturing decisions under the uncertainty of demand and recovery rate are obtained.

During the last decade, Game Theory (GT) has witnessed an increased interest from the PSE and management science communities, as its necessity to incorporate various decision-makers into the decision-making process increases. This can be seen from the proliferation of game-theoretic publications in SCM (Wang, 2005; Colson, Marcotte, & Savard, 2007; Li *et al.*, 2009; Leng & Parlar, 2010; Xiong *et al.*, 2013; Huang *et al.*, 2013; Yue & Fengqi, 2014).

Within GT perspective, enterprises contrasting or competing objectives are considered as game players. The objective function in GT is called payoff function in case of maximizing the profits, or loss function in case of minimizing the cost. The possible actions/reactions of the game players are referred as strategies. A game can be either a zero-sum-game or non-zero-sum game. For zero-sum-games, the amount gained by one player is the same as the amount lost by other players. In this case it is not possible to determine when a player should cooperate to obtain a cumulative benefit. For non-zero-sum games, the amount gained by one player is not the same as the amount lost by other players, so the gains of one player cannot be deduced from the gains of the others. The game can be considered as dynamic, when the game is repeated sequentially. This type of games are known in the literature as multi-stage games (Cachon & Netessine, 2004).

For non-cooperative games, game players seek, independently, to optimize their individual benefits. Nash Equilibrium (NE) (Nash, 1950) and Stackelberg (Stackelberg, 1934) games are approaches to solve non-cooperative games. NE is used when the roles of the game players are symmetric (i.e. no one is leading the game), and they simultaneously make their decisions. The NE solution is reached when none of the game players can improve her/his benefits by changing just her/his own strategy, unilaterally. On the other hand, the Stackelberg game can be played when the roles of the game players are not symmetric; one of the players is leading the game by playing the first move to achieve its best results taking into consideration that the other players are seeking the same objective.

Many works have been carried out to optimize decentralized SCs through GT based on non-cooperative cases. Wang (2005) develop a non-cooperative Stackelberg game model for a single buyer-single seller SC based on quantity discounts under the leading role of the seller. Li *et al.* (2009) propose an coordination contract for a manufacturer-retailer SC considering asymmetric information under the uncertainty of the price and demand. A Stackelebrg game is implemented under the leading role of the manufacturer. According to their approach, the leader proposes coordination option-contract. Leng and Parlar (2010) implement the Nash equilibrium game to obtain the optimal production levels of different competing suppliers around a single manufacturer in an assembly SC. They study different scenarios to identify the optimal production levels of each supplier and the retail price of the manufacturer. Huang *et al.* (2013) model the interaction between a manufacturer and different used products suppliers as a Stackelberg game under the leading role of the manufacturer in a decentralized reverse flow SC.

Yue and Fengqi (2014) analyze complex SC structure with different suppliers and retailers around a manufacturer. A non-cooperative Stackelberg game is implemented to model the interactions between the manufacturer (as leader) and the suppliers/retailers (as followers). They solve the competence between the different suppliers and retailers through a non-cooperative game based on generalized NE. The Stackleberg game model is formulated as a bi-level MINLP model with the manufacturer problem as the upper-level and the suppliers/customers problems as the lower-level. The bi-level model is simplified to MILP, and the lower-level LP problems are replaced by their KKT conditions in the upper-level problem. However, the competing suppliers are considered obliged to provide resources to the manufacturer disregarding the competition among different clients. This gives a dominant leadership to the manufacturer. Furthermore, in their proposed Stackelberg game bi-level model, the follower model has been simplified in order to be replaced in the leader model, thus losing practicality. The original model cannot resolved if the follower model in non-convex MINLP (Colson *et al.*, 2007). This simplification would not be realistic if the supplier participates as full SC. Moreover, their proposed approach disregards the uncertainty of all participants.

Table 2.2 summarizes the coordinated management literature review.

Table 2.2: Supply chain and integrated supply chain management literature

Authors	Cooperative approaches					non-Cooperative approaches									
	Multi-agent systems	Revenue-sharing	Cost-sharing	Backorder cost-sharing	Risk-sharing	Stackelebrg-game	Nash-Equilibrium game	Shortage penalty	Option-contracts	Buyback-contracts	Quanity flexibility contracts	Return-contracts	Rebate-contracts	Compensation-contracts	Backward-induction
Banaszewski *et al.* (2013)	✓														
Cao *et al.* (2007)	✓														
Cao *et al.* (2013)		✓				✓									
Govindan and Popiuc (2014)		✓													
He (2015)														✓	
Heese and Kemahlioglu-Ziya (2016)		✓													
Hennet and Arda (2008)				✓											
Huang *et al.* (2013)						✓									
Inderfurth and Clemens (2014)					✓										
Li *et al.* (2009)						✓			✓						
Li *et al.* (2013)								✓							
Lian and Deshmuck (2009)											✓				
Meca *et al.* (2004)			✓												
Moyaux *et al.* (2006)	✓														
Singh *et al.* (2014)	✓														
Taylor and Xiao (2009)												✓	✓		
Wang (2005)						✓									
Xiong *et al.* (2013)															✓
Yuan *et al.* (2013)	✓														
Yue and Fengqi (2014)						✓	✓								
Zhao *et al.* (2010)									✓						
Zhao *et al.* (2013)									✓						
Zhao *et al.* (2014)										✓					

Challenges in coordination management

However, current coordination methods, either for cooperative or non-cooperative cases, implicitly focus on simple SC structures, in which the negotiating players are forced to collaborate (no external providers/clients). None of the reviewed literature considers the standalone case of any of the participants, thus giving less flexibility to accept/reject the collaboration. Moreover, none of the reviewed literature evaluates the negotiation outcome based on the revenues probabilities and risk behavior. The coordination contract may lead to fundamental changes in the tactical decisions of of all participants, forming a challenge to be more explored and analyzed. Such an analysis requires the consideration of the reaction associated with the competing third parties which results from their unknown decision process and uncertain nature. The reviewed literature allows to provide individual decisions based on monopolistic situations, where decisions are imposed by one centralizing player without complete information about the other players or their reaction to the uncertain nature of their third parties. So, coordination/collaboration based on information sharing is needed to secure confident relationships between participants, thus, both share future risks, especially in an uncertain market environment. Effective negotiations able to capture the contrasting goals of all participants, including the third parties in the tactical decision-making process are needed towards optimal multi enterprise-wide coordination. Consequentially, many issues need more investigation, such as:

- Representing the negotiating partners with their full SCs.
- Comparing the coordination based on cooperative and non-cooperative cases.
- Considering external providers/clients (standalone case).
- Quantifying the probability of acceptance and willingness to collaborate
- Analyzing the effect of the uncertain reaction of each enterprise on the decision-making of all participants.
- Incorporating the uncertainty of the third parties in the negotiations.
- Analyzing the coordination effect on the tactical decision-making.
- Evaluating the coordination outcome.
- Considering the variations of the benefits scenarios around the mean.
- Coordinating real-sized complex decentralized SCs.
- Solving the game complex MINLP bi-level model without simplifying.

2.6 Thesis research challenges

Although PSE and OR literature have room for multi-enterprise coordination (M-EWC), a few works have been carried out to fill this room. New decision-support tools are needed towards efficient coordination management integrating the marketing decisions with the operational decisions, while keeping high business performance. After an extensive literature review, the coordination management in the chemical industry can be identified as the object of interest. Towards multi enterprise-wide coordination(M-EWC), the following challenges still require specific attention:

- Global Large-scale chemical industry SCs should be analyzed with detail description of all echelons, resources and information flows (transfer price, shared products, market conditions, duties, etc.). The dynamic interaction between these echelons, represented by their enterprises stakeholders should be also explored.

- Most of the reviewed literature focus on the coordination between different SC decision-making layers through integrated SCM. There is a need to investigate the inter-organizational coordination.

- SC tactical decision-makers use to construct the optimization models based on knowledge related to a centralizing decision-maker without knowledge about the interacting enterprises within the same SC of interest. By doing so, much information is lost, leading to sub-optimal decision-making. New modeling approaches based on knowledge sharing among all participants are vital to avoid SCs disruptions.

- Current SC tactical optimization models deal with the resources and information flows along its own SC echelons, minimizing the role of the complex behavior of third parties by representing them with fixed parameters (price, capacity, etc.). However, the decisions based on this picture are not sufficient when the third parties significantly affect these decisions, especially when a global coordination is to be established in a competitive uncertain environment. Specific incorporation of the third parties objectives in the tactical decision-making process should be addressed in depth.

- External resources prices have been regarded in the literature to represent the transaction relationships between centralizing partners and third parties rather than as a collaborative process. By doing so, the competition among the third parties is disregarded, which may lead to losing partners from the whole SC network. New decision-support tools able to treat the prices as collaborative/coordination outcomes are needed to guarantee mutual benefits for all participants.

- Since the third parties price policies are hard to model, the typical literature assumption is to use average approximation, so to simplify. Such simplification may lead to lose important information leading to inefficient coordination. Moreover, average price policy approximation may not be the optimal decision. New pricing approaches within the tactical management based on different price approximation possibilities are to be explored and compared with the traditional average approximation. The impact of these approaches on the tactical decision-making is to be explored.

- Multi-enterprise wide coordination is weakly dealt up today, especially for large-scale chemical industry SCs when a detailed master plan is to be established. None of the reviewed literature addresses the interaction between organizations as main partners participating as full SCs under uncertain competitive conditions in the presence of third parties. To avoid double marginalization, a new negotiation approach is needed to establish the best conditions for the coordination/collaboration contracts between the organizations of contrasting objectives.

- Usually, the decentralized SC decision-making process is carried out without considering the risk that may be faced due to the overlapping contrasting/competing decisions considering the uncertain reaction of other partners, especially when they all interact with competing third parties. This stresses on the need of effective coordination/collaboration that is able to capture these contrasting/competing objectives in a single approach.

- Current decision-support tools for decentralized SCs decision-making provides decisions based on cooperative or non-cooperative approaches. A methodological framework to analyze and compare both approaches on the same SC network is needed.

- Efficient uncertainty management is one of the challenging topics facing the PSE community due to the accompanied complexity. None of the reviewed literature considers the uncertain behavior of the third parties resulting from the dynamics of their price policies. This stresses on the necessity to develop new expected win-win coordination/collaboration approaches able to capture the uncertain reaction of the interacting enterprises resulted from the uncertain nature of their competing third parties.

- The reviewed literature addresses the coordination for simple SC structures, mostly supplier-retailer SCs, where none of them can function at the standalone case. There is a need to address the coordination for complex large-scale SC networks, where all participants can function at the standalone case. This leads to another challenge, which is quantifying the probability of acceptance or willingness to collaborate, which has not been quantified up to day.

- The reviewed literature provides single coordination contract without giving any flexibility to the negotiating partners to evaluate different options based on more information related to their risk behavior and preferences. Accordingly, a new coordination/collaboration framework that is able to provide different coordination contracts to cope with different risk behaviors. These coordination contracts must be able to represent the trade-off between the contrasting objectives from a holistic point of view.
- Due to the volatility of the global market, it is necessary to examine the relation between the SCs coordination/collaboration and the uncertainty reduction effect, and to analyze how this affects the enterprises players willingness to collaborate.
- Further research is needed to help enterprises decision-makers to evaluate and assess the effect of their response to the other partners choices taking into account the variability of their revenues scenarios around the mean.
- All of the reviewed literature bi-level approaches tempts to simplify the MINLP mathematical formulations of the follower model. New solution methods are to be explored, without simplifying, and implemented to real-data industrial cases.

Accordingly, and towards efficient multi-enterprise wide coordination (M-EWC), this thesis is developed to highlight these challenges through six main issues: i) global coordination, ii) integration of competitive third parties, iii) pricing approximation modeling, iv) cooperative vs. non-cooperative negotiations, v) non-cooperative dynamic negotiations, and vi) inter-organizational coordination using game theory.

2.7 Thesis objectives

As described above, up to this moment, there has not been proposed any quantitative methodology to coordinate various enterprises in a large-scale decentralized SC, considering the detailed description of each participant SC. There has not been proposed any decision-support tool that allows third parties to participate in the decision-making process as collaborative partners rather than external partners. Moreover, there has not been proposed any decision-support tool that quantifies the probability of acceptance of the players actions. Accordingly, the necessity to develop effective global tactical decision-making with effective coordination is increasing, especially in a highly competitive and uncertain situations.

The overall goal of this thesis is to develop different decision-support tools able to, holistically, optimize the tactical decisions of chemical industry large-scale multi-enterprise multi-product decentralized SCs taking into consideration the decisions of all participants. In order to achieve this overall goal, the following objectives are to be accomplished:

- To develop generic tactical decision-making models with detailed description of all participants.
- To propose partnership collaboration tools between enterprises and third parties, and to build and compare different price policies approximation models.
- To analyze and compare cooperative and non-cooperative collaborations, in comparison with the standalone system.
- To set the best conditions for inter-organizational coordination contracts under uncertainty, considering the uncertain reaction of one of the partners.
- To achieve inter-organizational coordination/collaboration through on game theory under uncertain and competitive circumstances.
- To study and compare the M-EWC role on the uncertainty reduction.
- To propose a coordination assessment strategy that copes with different decision-makers risk-behaviors.
- To study and compare the coordination effect on the tactical decisions of all participants.

2.8 Thesis outline

This thesis is structured bearing in mind the issues previously discussed. Figure 2.3 describes schematically the outline of this document.

This thesis document is divided into four parts. Part I includes this introductory view of the problem to be addressed (Chapter 1); a State-of-the-Art review, followed by emerging research challenges and objectives (Chapter 2), and the methods and tools utilized through this thesis (Chapter 3)

Part II and Part III represent the main body of this thesis. Part II deals with the global coordination of large-scale chemical industry SCs with their supporting organizations (third parties) from a tactical management point of view. For this purpose, Chapter 4 proposes generic global tactical model coordinating the resources flows to/from the third parties under the global coordinated SC overall objective function. Here, the third parties participate in the global tactical decision-making process with their detailed characteristics as full SCs management problems. Chapter 5 deals with the global coordination of large-scale SCs surrounded by competitive third parties. A novel coordinated framework is proposed considering the price policies as joint collaboration tools within the overall decision-making process. Then, this framework is extended to propose and compare different price policies approximations models based on the traditional average approximation and discounting approaches.

Part III extends the global coordination framework developed in Part II to address the inter-organizational coordination between several participating organizations of contrasting and competitive objectives, as full SCs, in the system of interest, with their competitive third parties under uncertainty. In Chapter 6, cooperative and non-cooperative collaboration approaches are analyzed and compared. Then, a novel scenario-based dynamic negotiation (SBDN) approach is proposed as a coordination/collaboration new methodology built on expected win-win principles; risk behavior; and probability of acceptance. The competitive third parties participate in the proposed SBDN approach with their price policies based on Chapter 5 and their uncertain nature.

In Chapter 7, the inter-organizational coordination is achieved using a novel integrated game theory approach. A Stackelberg and Nash Equilibrium games are implemented to capture the contrasting and competitive objectives between the participating enterprises considering the uncertain behavior of all participants. In Part III, the uncertainty is tackled through Monte-Carlo Sampling method. To end this part, a set of coordination contracts is proposed and compared as a novel Stackelberg set of Pareto frontiers.

Finally, Part IV includes Chapter 8, which summarizes the thesis contributions and outcomes, and draws emerging concluding remarks for future work.

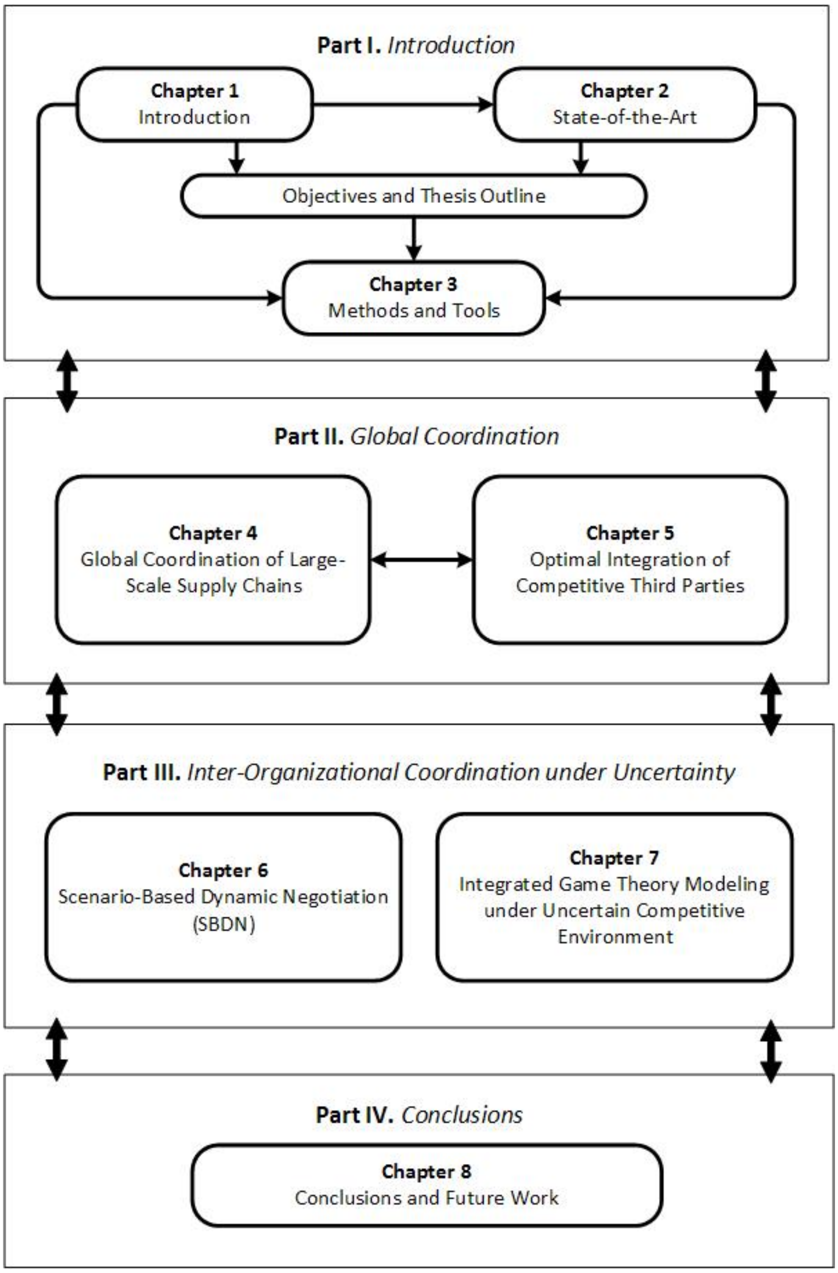


Figure 2.3: Thesis outline

Chapter 3

Methods and Tools

3.1 Introduction

The major aim of the PSE community is to develop decision-support tools to help, systematically, chemical industry enterprises to effectively optimize their industry, from the molecular size (Sahinidis & Tawarmalani, 2000; Achenie, Gani, & Venkatasubramanian, 2002; Gani & Ng, 2015); product design (Subramanian, Pekny, Reklaitis, & Blau, 2003; Smith & Ierapepritou, 2011); experiment design (Telen, Vercammen, Logist, & Impe, 2014); up to SCM (You & Grossmann, 2011; Cafaro & Grossmann, 2014).

The multi-enterprise wide coordination (M-EWC) problems tackled in this thesis are complex and require quick response to the volatile markets, so it implies the use of efficient methods and tools. In this chapter, the decision-making tools used for developing the tactical optimization models throughout this thesis are illustrated. The theoretical concepts of these tools and their implementations in the chemical process industry are discussed. First, the current optimization approaches are illustrated, followed by analyzing the different programming methods and solvers. Then, the decision-making approaches under uncertainty, multi-objective optimization, and game theory are described.

3.2 Decision making

Different decision-making approaches are implemented to identify the best decisions, usually classified as descriptive or normative approaches (Bell, Raiffa, & Tversky, 1999).

3.2.1 Descriptive approaches

Descriptive decision-making approaches are concerned with identifying the observed nature of a problem. However, descriptive approaches do not do not concern about solving the problem. Among the descriptive approaches used are: i) forecasting, and ii) simulation methods.

i) Forecasting: this method is based on future projections of what will happen in the future such as (market demands, supply, price, etc.). Such a method is highly empirical, and needs much statistical analysis.

ii) Simulation: the user simulate the behavior of a system with different degrees of accuracy to imitate a real system. The user fixes the system parameters while keeping checking the feasibility. Although simulation methods provide the best performance of a system, it does not optimize it.

3.2.2 Normative approaches

Normative approaches are concerned with solving a problem based on a set of rules using mathematical programming or heuristic techniques .

Mathematical programming

Mathematical programming methods seek to optimize the decision-making problems based on real or integer variables within constraints.

Heuristic methods

Heuristic methods are based on feasible approximate solutions, but they do not guarantee optimality. Among the heuristic methods are: i) Lagrangian heuristics, and ii) Meta-heuristics.

i) Lagrangian heuristics (relaxation) are based on finding the problem solution based on iterations. The first solution point is obtained for the optimization problem. Then, different iterations are trained to find the feasible ones around the first solution within upper and lower bounds. When the gap between the best upper and lower bounds is near to a certain value, the local optima is found.

ii) Meta-heuristics are based on finding a solution space using robust stochastic methods. Among the current meta-heuristic algorithms are genetic algorithms, tabu search, hyper-heuristics, path relinking, neural networks, simulated annealing, scatter search, ant colony optimization, etc.

3.3 Optimization methods and tools

The optimization process aims to maximize or minimize a performance metric of a system with degree of freedom variables under different quality and inequality constraints. Decisions can be taken based on the resulting optimal performance. To optimize the chemical process industry SCs, decision-support tools and modeling techniques are required at different enterprise investment levels (design, operation, and control). To construct an optimization mathematical model, four main elements have to be identified:

- **Objective function**: the main goal of the enterprise (e.g. maximize revenues, minimize cost, minimize environmental impact, maximize social benefits, etc.).

- **Degree of freedom variables**: the independent variables (continuous, semi-continuous, and discrete) such as production levels, storage amounts, open or close facility/unit, prices, etc.

- **Parameters**: available data such as customer demands, unit costs, efficiencies, distances, capacities, production recipes, etc.

- **Equality constraints**: such as mass balances, purchase, production, inventory capacity limits, correlations between variables, etc.

The optimization can be continuous or discrete. Continuous optimization problems include continuous degree of freedom variables. Discrete optimization problems involve binary (integer) variables (e.g.: yes/no decisions, open/close facility, equipment allocation, price allocation to demand, etc.). The optimal decisions of the optimization problems are the best values of the degree of freedom variables that satisfy the problem constraints.

The mathematical formulations of the optimization problems result in different programming models:

3.3.1 Linear programming (LP)

Linear programming (LP) is a continuous mathematical program with linear correlated variables. Eq. (3.1) illustrates a LP optimization problem with a profit maximization objective function. x represents the continuous decision variables; *g(x)* and *h(x)* represent the equality and inequality constraints, respectively. The problem is LP when the functions *Z(x)*, *g(x)*, and *h(x)* are linear.

$$\max_{x \in X \subset \mathbb{R}^n} Z(x) \begin{cases} h(x) = 0, & h : \mathbb{R}^n \longrightarrow \mathbb{R}^l \\ \\ g(x) \leq 0, & g : \mathbb{R}^n \longrightarrow \mathbb{R}^m \end{cases} \tag{3.1}$$

The feasible region of a LP problem is called "polyhedron S". To solve LP problems, i number of iterations are required to solve i number of constraints.

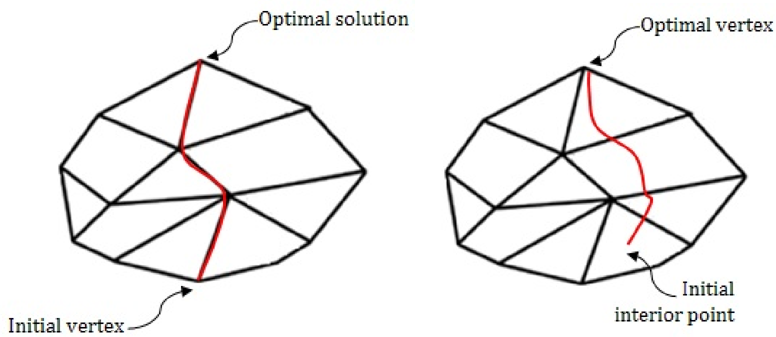
Two solution methods are used to solve LP problems: i) the simplex method (Dantzig, 1951, 1963), and ii) interior point method (Gonzaga, 1992; Marriot & Hallo, 1998).

i) Simplex method

The simplex method (vertex-following) is based on finding the optima on the polyhedron S by moving from one vertex (corner) to another vertex. The simplex algorithm starts from testing the optimality of an initial solution vertex. If it is not optimal, the algorithm identifies adjacent vertex and the optimality is tested again until finding the optima (Figure 3.1(a)). More information can be found in Dantzig (1963).

ii) Interior-point methods

The interior-point method is based on searching through the interior of the feasible region S using iterations without touching the border. An initial feasible interior point is assumed, then the search for the optimal solution (vertex) is started from the interior moving through the possible feasible region (Figure 3.1(b)). Further details can be found in Marriot and Hallo (1998).



(a) Simplex method (b) Interior point method

Figure 3.1: LP solution methods

3.3.2 Mixed-integer programming (MIP)

Mixed-integer programming (MIP) results from problems with binary variables, logical conditions (and, or, not, etc.), or special ordered sets (sets of non-zero values). MILP models results from enterprise-wide optimization (EWO) problems such as discontinuous operations and scheduling (Floudas & Lin, 2004; Méndez, Cerdá, Grossmann, Harjunkoski, & Fahl, 2006; Shah & Ierapetritou, 2015; Bindlish, 2016) logistics and multi-period optimization (Grossmann, 2005; Gebreslassie, Yao, & You, 2012), and linear approximations (piecewise) of complex non-linear problems.

MIP problems can be represented by Eq. (3.2), where c, b, and d are coefficients vectors, and A and B are the coefficients matrices. x and y represent the continuous and discrete variables, respectively.

$$\max Z(x,y) = cy + dx \begin{cases} Ay + Bx \leq b \\ x \in X \subset \mathbb{R}^n \\ y \in Y \subset \mathbb{Z}^m \end{cases} \tag{3.2}$$

The methods to solve MILP problems are enumerative algorithms based on pruning criteria. This means that not all feasible solutions are tested for optimality. The solution times of MILP programs depend on the model formulation; the use of redundant constraints may help in reducing the computational time. Different algorithms are used to solve MILP problems: i) Branch and Bound (B&B) algorithm, and ii) Branch & Cut (B&C) algorithm.

i) Branch and Bound (B&B) algorithm

Branch & Bound (B&B) algorithm with LP-relaxation (Land & Doig, 1960) is widely used to solve MILP problems. B&B algorithm is a tree search method, in which the original problem is partitioned (divide and conquer) into continuous sub-problems. For example, for maximization problems, lower bounds are used during the optimization process to avoid extensive searches in the feasible tree space. All discrete variables are relaxed to continuous variables, and the first node "tree root node" is established from solving the relaxed LP problem. The branching then starts to search for sub-problems and compare the results until finding the optima.

Dakin (1965) extends the B&B algorithm considering three criteria: infeasibility, optimality, and value dominance. The branching and dividing the solution space is based on creating nodes with additional constraints on lower and upper bounds. The algorithm accepts a new integer solution if it is better than the old one by at least a specific value. The branching starts when the pruning criteria fail.

Different search strategies are used for B&B algorithms such as depth-first and back-tracking rule methods. The search terminates if the solution space of the LP-relaxation is bounded.

ii) Branch & Cut (B&C) methods

One of the important issues for solving MILP problems is tracing infeasibility. Branch & Cut (B&C) algorithm (Padberg & Rinaldi, 1987) can be used alternatively or additionally to the B&B algorithm to solve MILP problems. When the LP-relaxation problem finds an optimal, new cutting planes (linear valid inequalities) are added to the linear relaxations, so that the size of the feasible space is reduced without eliminating integer solutions. This forces the non-integer variables of the relaxed solutions to take integer values (Kallrath, 2000).

Many solvers are used to solve MILP problems such as CPLEX, XPRESS, GUROBI, etc. In this thesis, the CPLEX solver is used to solve MILP models due to its sophisticated solution packages and ability to give solutions in less computational time.

3.3.3 Non-linear programming (NLP)

For the optimization problem as in Eq. (3.1), if any of the functions *Z(x)* or any of the constraints functions *h(x)* and *g(x)* is nonlinear, the problem is considered as a NLP problem. The presence of nonlinearities is very common in the PSE problems, such as the reaction kinetics of the chemical processes (i.e. batch process synthesis, flows, etc.), pricing models, etc. The complexity of the NLP problems arises when solving the convergence resulting in many local optimals. For convex NLP problems, the local minimum is equal to the global minimum.

Lagrangian method (Kuhn & Tucker, 1951) is used to solve NLP problems with equality and inequality constraints. Lagrangian method is based on transforming the problem into an unconstrained model using the Lagrangian multipliers λ and μ as in Eq. (3.3).

$$\mathcal{L}(x, \lambda, \mu) = Z(x) + \lambda h(x) - \mu g(x) \qquad \forall \lambda \in \mathbb{R}^n; \mu \in \mathbb{R}^l \tag{3.3}$$

Many algorithms are used to solve NLP optimization problems with high number of inequality constraints, such as generalized reduced optimization algorithm (GRG) (Abadie & Carpenter, 1969; Abadie, 1978), sequential quadratic programming (SQP) (Fletcher, 1987), and interior point method (IPM) (Wright, 1996). For problems with low nonlinear terms, sequential linear programming (SLP) can be used.

Many solvers are used to solve NLP problems such as MINOS, CONOPT, IPOT, KNITRO, etc. In this thesis, the CONOPT solver is used to solve the developed NLP models. More review about NLP algorithms and solution techniques can be found in Biegler (2010).

3.3.4 Mixed integer non-linear programming (MINLP)

Mixed integer non-linear programming (MINLP) tackles optimization problems with nonlinear and integer variables (Eq. (3.4)). The vector $x = (x1, x2, ..., x_n)$ represents the n continuous variables, and the vector $y = (y1, y2, ..., y_m)$ represents the m discrete variables. The problem is considered as MINLP when there is nonlinearity in one of the functions $Z(x, y)$, $h(x, y)$, and $g(x, y)$.

A feasible solution is obtained when any augmented vector $\vartheta = x \bigoplus y$ satisfies the constraints of Eq. (3.4). Any feasible solution leads to objective function more than or equal to the feasible solutions can be considered as an optimal solution. This means that the problem might lead to more than one optimum.

$$maxZ(x, y) \begin{cases} x \in X \subset \mathbb{R}^n \\ y \in Y \subset \mathbb{Z}^m \\ h(x, y) = 0 \\ g(x, y) \leq 0 \end{cases} \tag{3.4}$$

The complexity of the MINLP problems arises from the non-convexity of the feasible region and the objective function. Different methods are used to solve MINLP problems such as:

i) Branch & Bound (B&B)

Branch & Bound (B&B) (Gupta & Ravindran, 1985) is based on building a search tree. The integer variables are relaxed as first step, then the solution of the relaxed problem is considered as lower bound (for minimization problems), so that the search tree is built.

ii) Generalized Benders Decomposition (GBD)

The generalized benders decomposition (GBD) algorithm (Geoffrion, 1972) is based on dividing the MINLP non-conve problem into two spaces: complicating and non-complicating variables spaces. The binary variables are classified as complicating variables. Then the problem is divided into a sequence of NLP sub-problems (by fixing the binary variables), and MILP master problems. The NLP sub-problems generate the upper bounds of the problem, and the MILP master problems generate a combination of discrete variables to be used as lower-bounds for the NLP sub-problems. The optimal solution then can be found when the upper and lower bounds match.

iii) Outer-Approximation (OA)

The Outer-Approximation (OA) algorithm (Duran & Grossmann, 1986) is based on dividing the MINLP non-convex problem into NLP sub-problems and MILP master problems. A feasible region is defined by the optimal solutions of the NLP sub-problems. The master problems are generated by approximating the non-linear constraints of the NLP sub-problems optimal solutions (feasible region).

Although, the interest arises to solve MINLP problems, still finding the global optima of non-convex MINLP problems is a challenge. Different solvers are used to solve convex and non-convex MINLP problems, such as: DICOPT (convex/non-convex), GloMIQO (convex/non-convex cuadratic), SBB (convex), BARON (convex/non-convex), SCIP (convex/non-convex), etc.

In this thesis, most of the developed mathematical models are non-convex MINLP, so to reflect real and practical applications. DICOPT and GloMIQO solvers are used through the General Algebraic Modeling System (GAMS). Initial solutions are provided to the problem to help finding the optima in less computational time.

3.4 Bi-level optimization

The bi-level optimization deals with the optimization of two problems simultaneously: an upper-level problem and a lower-level problem. The idea of the bi-level formulation is that the upper-level optimization model is solved taking into consideration the optimal solution of the lower-level problem, as both are solved simultaneously (the lower-level problem is embedded as constraints in the upper-level problem).

Eq. (3.5) represents a typical bi-level optimization problem. The terms $Z(x, y)$ and $z(x, y)$ are the upper-level and lower-level objective functions, respectively. X and Y represent the upper-level and lower-level decision variables; $G(x, y)$ and $H(x, y)$ represent the upper-level inequality and equality constraints, while $g(x, y)$ and $h(x, y)$ represent the lower-level inequality and equality constraints. It can be noticed that the constraints of the upper-level problem depend on both the upper-level and the lower levels decision variables (x and y).

$$\begin{gathered}
\max_{x \in X, y} Z(x, y) \begin{cases} H(x, y) = 0 \\ G(x, y) \leq 0 \end{cases} \\
where, \\
y \in \max_{y \in Y, x} z(x, y) \begin{cases} h(x, y) = 0 \\ g(x, y) \leq 0 \end{cases}
\end{gathered} \tag{3.5}$$

In case the lower-level problem results in a convex and regular model formulation, it can be replaced by its Karush-Kuhn-Tucker (KKT) conditions (Kuhn & Tucker, 1951), thus transforming it into constraints in the upper-level optimization model (Eq. (3.6)). This reformulation results in a monolithic model (single-level formulation) that can be solved at once. The vectors $\lambda \in \mathbb{R}^m$ and $\mu \in \mathbb{R}^l$ are the KKT multipliers.

$$\begin{gathered} \nabla z(x,y) + \sum_{i=1}^{m} \lambda_i \nabla + h_j(x,y) + \sum_{j=1}^{l} \mu_j \nabla g_j(x,y) = 0 \\ h_i(x,y) = 0, \quad g_j(x,y) \leq 0, \\ \lambda_i \geq 0, \quad \mu_j \geq 0 \qquad \forall i \in m; j \in l \end{gathered} \tag{3.6}$$

When the model does not have inequality constraints $m = 0$, then the KKT multipliers turns into the Lagrange multipliers (see Eq. (3.3)). However, bi-level optimization problems are limited to small-size problems up to date. Solving large-scale non-convex MINLP bi-level models is still a challenging research topic. In this thesis, the developed bi-level MINLP models are solved using iterations scenarios, as will be seen in Chapters 6 & 7.

3.5 Game theory

Game Theory (GT) is used to solve the interaction between different enterprises decision-makers sharing some interests. During the last few years, GT has witnessed an increasing interest of the PSE community, as its necessity to incorporate various actors into the decision-making process increases. This can be seen from the proliferation of GT publications, especially in SCM (Cachon, 2003; Cachon & Netessine, 2004; Wang, 2005; Hennet & Arda, 2008; Leng & Parlar, 2010; Zhao *et al.*, 2010; Li *et al.*, 2013; Yue & Fengqi, 2014; Chu, You, Wassick, & Agarwal, 2015; Ramos, Boix, Aussel, Montastruc, & Domenech, 2016).

Within GT, stakeholders of contrasting and competitive objectives are considered as game players. The performance metric is called "payoff function" in case of maximizing the profits, or "loss function" in case of minimizing the cost. The possible actions and reactions of the game players are named as the game strategies. Depending on the interaction among the different game players, the game is classified as cooperative or non-cooperative game.

Cooperative games: the game players are supposed to agree on forming a coalition towards the optimization of a shared objective function under a given set of conditions.

Non-cooperative games: the game players seek, independently, to optimize their individual payoffs.

A game can be zero-sum-game, non-zero-sum game, or dynamic game:

Zero-sum-game: the amount gained by one game player is the same as the amount lost by the other game player. In this case, a cumulate revenue is not possible from their cooperation.

Non-zero-sum game: the amount gained by one game player is not equal to the amount lost by the other game player/s. This means that the gains of one player cannot be deduced from the gains of the other players.

Dynamic game: or "multi-stage game" is when the game is repeated sequentially.

In this thesis, non-cooperative games (Stackleberg and Nash Equilibrium games) are implemented and solved for the coordination between the negotiating enterprises stakeholders in an uncertain competitive environment.

3.5.1 Nash Equilibrium (NE)

Nash Equilibrium (NE) (Nash, 1950) is implemented for non-cooperative games when the roles of the game players are symmetric (i.e. no one is leading the game). Within NE games, the game players make their actions (decisions), simultaneously. The NE equilibria is obtained when none of the game players can improve her/his payoffs by changing just her/his own strategy, unilaterally.

Eq. (3.7) illustrates the NE mathematical formulation; $i \in 1, 2, ..., I$ represents the number of the NE-game players; k_i represents the strategy of player i, and k_{-i} represents the strategy of the rest of the NE game players (all players except player i); Z_i is the objective function of player i.

$$\max_{k} Z_i(k_i, k_{-i}) \qquad \forall i \in I \tag{3.7}$$

The NE-game equilibria strategy k^* is achieved when none of the game players i can improve her/his payoffs by changing only her/his own strategy k_i (Eq. (3.8)).

$$Z_i(k_i^*, k_{-i}^*) \geq Z_i(k_i, k_{-i}^*) \qquad \forall i \in I \tag{3.8}$$

Dilemma example

One of the famous NE-game examples is the dilemma case. The NE-game players decide between collaborating or not (Figure 3.2). To find the NE-equilibria, we have to analyze all the movements (possible strategies). If player 1 decides to collaborate, player 2 best response will be to collaborate, as she/he will get 5 units instead of zero. If player 1 decides not to collaborate, the best response of player 2 will be to collaborate (payoff 15 units). If player 2 decides either to collaborate or not, player 1 must collaborate. So the NE-equilibria between both of them is to collaborate.

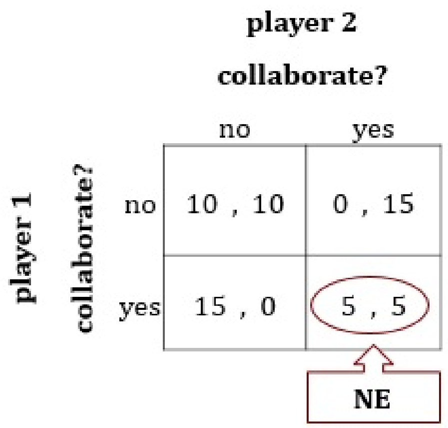


Figure 3.2: NE-game: Dilemma example

3.5.2 Stackleberg game

The Stackelberg game (Stackelberg, 1934) can be played between stakeholders of contrasting objectives within a non-cooperative framework, and their roles are not symmetric. That is, one of the Stackelberg game players makes the first game move; this player who is leading the game is called "Stackelberg-game leader", and the others are called as "Stackelberg-game followers".

Mathematically, a single-leader single-follower Stackelberg game forms a bi-level model (Colson *et al.*, 2007), where the leader model is considered at the upper-level problem, and the follower model is considered at the lower-level problem. In this case, the leader makes actions taking into consideration the optimal response of the follower, as both the upper-level and the lower-level problems are solved simultaneously (see Eq.(3.5)).

However, when the lower-level problem is non-convex, it is impossible to be replaced using the KKT conditions method (Bard, 1998; Colson *et al.*, 2007).

In this thesis, the proposed Stackelberg-game models are built as bi-level models, with non-convex MINLP upper-level and lower-levels problems. Another solution methodology is proposed without simplifying.

If the Stackelberg-game is implemented to the Dilemma example with player 2 as the leader. The Stackelberg-game equilibrium will be, the same as the NE, when both collaborate (Figure 3.3).

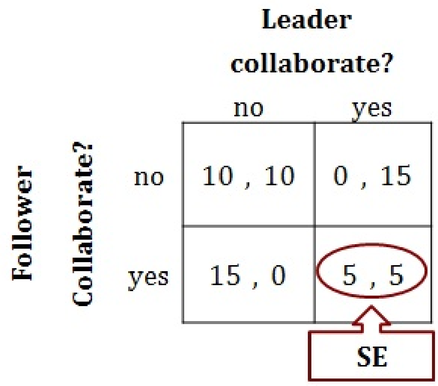


Figure 3.3: Stackelberg-game Equilibrium

3.6 Multi-objective optimization

Multi-objective optimization (MOO) or "vector optimization" refers to the optimization considering, simultaneously, multiple objectives resulting from introducing new issues such as social, environmental and risk regimes as part of the optimization objective functions together with the economic objectives. EWO problems involve multiple conflicting objectives, in which the trade-offs between those conflicting objectives, which is often analyzed as a Pareto of solutions, affects the decision-making process.

Eq. (3.9) describes the general mathematical formulation of a MOO problem: X represents the solution vectors (feasible space).

$$max_{x \in X}(Z_1(x), Z_2(x), ..., Z_n(x)) \qquad n \geq 2, Z : X \longrightarrow \mathbb{R}^n \tag{3.9}$$

The Pareto of solutions is identified based on the dominance concept (Messac, Ismail-Yahaya, & Mattson, 2003; Deb, 2008). A solution $x_1 \in X$ is a **Pareto** solution when $x_1 \in X$ dominates $x_2 \in X$ if:

1. $Z_i(x_1) \geq Z_i(x_2) \qquad \forall i \in n$ (for all objective functions) and

2. $Z_i(x_1) > Z_i(x_2)$ at least $j \in n$ (for at least one objective function)

Different approaches are used to solve MOO problems such as $\epsilon-constraint$ (Messac *et al.*, 2003), goal programming (Charnes & Cooper, 1961), multi-parametric programming (Pistikopoulos, Galindo, & Dua, 2007; Oberdieck & Pistikopoulosb, 2016), wighted-sum (Fishburn, 1967; Triantaphyllou, 2000), metaheuristics through genetic algorithm (Lin, Fowler, & Pfund, 2013), lexicographic minimax (Liu & Papageorgiou, 2013), and surrogate modelling (Beck, Friedrich, Brandani, & Fraga, 2015).

However, the current MOO approaches focus on the objectives of one organization without considering the different objective functions of different participating organizations in the system of study. In this thesis, the different individual objective functions are considered when optimizing large-scale multi-enterprise SCs.

3.7 Decision-making under uncertainty

Due to the SC dynamics and the volatility of the markets, the presence of uncertainty is one of the basic characteristics of EWO problems. Enterprises managers usually take decisions based on the assumptions that all information is known. However, robust responsiveness through considering uncertainty explicitly is a must in order to guarantee efficient capacity utilization, market competitiveness, and efficient infrastructure decisions (Papageorgiou, 2009).

Uncertainty sources can be classified as: i) exogenous (e.g. demand, supply, etc.), and ii) endogenous (e.g. yield, capacity, etc.) (Jonsbraten, Wets, & Woodruff, 1998). The trend of considering uncertainty is based on forecasting the behavior of the uncertainty sources based on current situation data using future projections. Two main approaches are implemented to address uncertainty: i) reactive, and ii) preventive approaches (Li & Ierapetritou, 2007).

3.7.1 Reactive approaches

Using the reactive approaches, the deterministic model is modified to react and respond to the uncertain events. Reacting with unexpected events may lead to re-scheduling or re-planning decisions. Heuristics and intelligent agents-based methodologies are often used to modify the deterministic models due to their short computational times. Two main methods are used to solve reactive problems: i) model predictive control, and ii) multi-parametric programming.

i) Model predictive control

Model predictive control (MPC) formulations anticipate the process performance and control variables through integrating optimal control, stochastic control, and process control systems within the future preferences (Camacho

& Bordons, 1995). MPC algorithm allows to optimize the control model (usually dynamic) in function of the forecasted future control variables considering a finite time-horizon. The length of the time horizon affects the efficiency of the solutions; longer horizons lead to more efficient solutions, but with higher computational efforts (Geyer, 2011; Tan, Tippett, & Bao, 2016).

MPC has many applications in EWO within the context of SCM due to its ability to predict the system behavior and deal with disturbances. Wang, Rivera, and Kempf (2007) propose a MPC-based decision model for the tactical planning of a semiconductors manufacturing SC under uncertainty of the RM supply and market demand. The MPC controllers predict the system performance by forecasting the future supply and demand. Alessandri, Gaggero, and Tonelli (2011) implement the MPC to a real-time tactical transport model. Lopez-Negrete, D'Amato, Biegler, and Kumara (2013) propose a fast non-linear MPC (NMPC) model for on-line non-linear dynamic real-time optimization. They use NLP sensitivity to compute fast approximations of non-linear solutions. They prove that the combination method leads to the same efficiency but with less computational time comparing with the original MPC. Niu, Zhao, Xu, Shao, and Qian (2013) implement the MPC to control the inventory under the uncertainty of demand. They consider the inventory decisions as control variables and the pricing as manipulated variables. For multi-time scale systems, Tan *et al.* (2016) implement the MPC with non-uniformly spaced optimization horizon for multi-time scale dynamic processes.

However, MPC algorithms require high computational efforts, especially for on-line non-linear and close-loop MPC with fast sampling rates. To reduce the computational efforts, MPC has been combined with multi-parametric programming (Bemporad, Borrelli, & Morari, 2002; Pistikopoulos *et al.*, 2007; Krieger & Pistikopoulos, 2014; Rivotti & Pistikopoulos, 2015) based on disassembling the original MPC problem into smaller problems and solving each of them as a multi-parametric programming problem.

ii) Multi-parametric programming

Multi-parametric programming is used as an optimization technique to define the optimal solution profile (or solution map) of a problem as a function of the uncertain varying parameters (Pistikopoulos, 2009). Eq. (3.10) illustrates the typical multi-parametric programming formulations, in which $f(x, \phi)$ is the objective function; $x \in X$ is the vector of optimization variables, $\phi \in \Theta$ is the parameters vector, and Θ is the parameter space.

$$Z(\phi) = max_{x \in X \subset \mathbb{R}^n} f(x, \phi)$$
$$g(x, \phi) \leq 0 \tag{3.10}$$
$$\phi \in \Theta \subset \mathbb{R}^m$$

Multi-parametric programming has many applications in PSE within different contexts such as: bi-level programming (Domínguez & poulos, 2010), constrained dynamic programming (Rivotti & Pistikopoulos, 2014), MPC (Krieger & Pistikopoulos, 2014), MOO (Oberdieck & Pistikopoulosb, 2016).

Domínguez and poulos (2010) use multi-parametric programming algorithm to solve integer and mixed-integer bilevel programming problems. They represent the integer and continuous variables of the lower-level problem as linear or polynomial terms in the upper-level problem. Then they reformulate the convex non-linear terms using linearization techniques to employ a continuous multi-parametric programming algorithm. Rivotti and Pistikopoulos (2014) propose a multi-parametric programming approach to solve multi-stage MILP inventory scheduling problem within the constrained dynamic programming context. they decompose the problem into a set of multi-parametric programming MILP problems to be solved sequentially in order to obtain the global optimal solution. Krieger and Pistikopoulos (2014) integrate the multi-parametric programming with the MPC algorithm through online parametric estimation. They prove that the integrated algorithm leads to better performance compared with the nominal MPC, according to the context of their paper. Oberdieck and Pistikopoulosb (2016) propose an approximation algorithm based on multi-parametric programming to calculate the explicit Pareto frontier for convex quadratic MOO problems with linear constraints.

Nevertheless, mitigating uncertainty is not always associated to the reaction to the random events, this needs also incorporating already deterministic information in the model formulation.

3.7.2 Preventive approaches

Unlike the reactive approaches, preventive approaches incorporate the uncertain parameters in the optimization models based on their forecasted behavior.

There are several preventive techniques to tackle uncertainty such as: i) Stochastic programming, ii) Chance-constrained programming, iii) fuzzy programming, and iv) robust optimization, amongst others.

i) Stochastic programming

Stochastic programming is the most commonly preventive technique to tackle uncertainty. Within stochastic programming, SCs' enterprises set their constraints based on optimizing the expected performance metric (minimize expected cost, maximize expected profit, etc.). As a scenario-based approach, the uncertain parameters as included as random scenarios (e.g. demand, price, yield, etc.) in terms of their probability distribution (Sahinidis, 2004). The purpose of the stochastic programming is to obtain the optimal expected decisions that are able to hedge against the average of the uncertain events.

According to the sequence of the uncertain events, stochastic programming can be two-stage or multi-stage stochastic programming. Within two-stage stochastic programing (2-SSP), the decisions are divided into first stage decisions and second stage decisions. The first stage decisions are made before the uncertainty revealing (here and now), while the second stage decisions are made when the uncertainty events reveals (recourse-wait and see). Stochastic programming can be multi-stage when the uncertain events reveal in multiple stages, sequentially, in which decisions are made over a sequence of periods.

Eq. (3.11) represents the general formulation of 2SSP problems: ξ represents the random vector of the uncertain data; $S(x, \xi)$ represents the set of the optimal second-stage decision variables (expected decisions).

$$max_{x \in X \subset \mathbb{R}^n} G(x) = f(x) + E[S(x, \xi)] \tag{3.11}$$

Stochastic programming has been implemented to different PSE problems. Tsiakis, Shah, and Pantelides (2001) develop a 2-SSP MILP design-planning model for a multi-echelon SC subjected to demand uncertainty. Gupta and Maranas (2003) develop a bi-level stochastic planning model under uncertainty of demand. Cheng, Subrahmanian, and Westerberg (2003) propose a 2-SSP multi-period SC design-planning model considering the uncertainty of technology availability and demand. They model the uncertainty of technology availability as a Markov chain, and the demands with probability distribution.

For large scale problems, a stochastic programming model has been proposed by Santoso, Ahmed, Goetschalckx, and Shapiro (2005), who integrate the accelerated Benders decomposition algorithm with the sample average approximation (SAA) method for the SC stochastic design model with continuous distributions for the uncertain parameters.

For petrochemical SCs, a 2-SSP MINLP design optimization model is proposed by Al-Qahtani, Elkamel, and Ponnambalam (2008) considering the uncertainty of process yield, raw material cost, retail price, and market demand. They consider the risk in terms of profit variability in the objective function.

You, Wassick, and Grossmann (2009) develop a 2-SSP multi-period planning model under the uncertainty of demand and freight rate. They evaluate the potential improvement of using stochastic programming by implementing a rolling horizon approach. You and Grossmann (2011) propose a MINLP design model integrating stochastic inventory under supply and demand uncertainties. The authors model the demand and supply variations, and develop an equivalent deterministic optimization model under the objective function of maximizing the net present value (NPV). They evaluate the SC responsiveness to the market demand scenarios through the expected lead time.

For closed-loop SCs, Baptista, Gomes, and Barbosa-Póvoa (2012) propose a 2-SSP closed-loop model under uncertainty of demand. They solve the large-scale stochastic model using L-shaped method.

For resilient SCs, García-Herreros *et al.* (2014) develop a 2-SSP model for the optimal design-planning of resilient SCs considering disruption probabilities of products demands. The selection and location of the distribution centers are considered as the first-stage variables, while the resources flows are considered as the second-stage variables.are assigned to each facility.

However, stochastic models deal with the random values of the performance scenarios as average. Even if they consider the variance, the impact of the differences between these scenarios is still neglected, as they deal equally with the performance values around the mean.

In this thesis, the average of the performance scenarios is not considered as evaluation criteria of the proposed coordination contracts. Instead, the probability of acceptance is calculated to reflect the impact of each performance scenario on the decision-making of all participants. Furthermore, the uncertainty of 3rd parties and its effects on the global decision-making is also addressed in this thesis.

ii) Chance-constrained programming

Chance-constrained or probabilistic constrained programming Charnes and Cooper (1959) tackles uncertainty by modeling the reliability of the solutions. The methodology is based on determining a certain confidence level (probability level), in which some of the model constraints are bounded by this level. This is applied to avoid the complexity resulted from the use of stochastic second-stage actions and the violation of constraints (Arrellano-Garcia & Wozny, 2009; Mesfin & Shuhaimi, 2010; Ross, Kuzu, & Li, 2016).

Arrellano-Garcia and Wozny (2009) propose a chance-constrained programming method for a large-scale nonlinear dynamic optimization problem of reactive batch distillation processes. In their model, some of the constraints are bounded by a predefined confidence level, which is computed by bounding a feasible region of the uncertain input variables. The output feasible region is mapped and the trade-off between robustness and profitability is analyzed. Later on, Mesfin and Shuhaimi (2010) propose a linear steady state chance-constrained model with single and joint chance constraints. Their model is applied to optimize a gas processing plant subjected to composition and feed flow rate uncertainties. Their chance-constrained model is converted to its equivalent deterministic model. According to the context of their approach, the chance-constrained formulations lead to better performance than the two-stage stochastic and worst-case approaches.

Considering the supplier-buyer relationship, Ross *et al.* (2016) implement the chance-constrained programming method for the supplier evaluation under disruptions in the supplier delivery. They consider the supplier on-time-delivery disruption risk scenarios as the supplier performance risk metric. However, their work can be extended to consider other risk performance metrics considering the disruptions from the buyer side. Furthermore, the conflicting objectives on the transfer price between the supplier and the buyer are not analyzed in their work, which will be the main focus of this thesis.

Comparing with the fuzzy programming, Cao, Gu, and Xin (2009) propose a MINLP chance-constrained and fuzzy programming models for the scheduling of refinery crude oil problem under the uncertainty of crude oil blinds demands. To simplify the computational efforts, they transform the chance-constrained model into its equivalent stochastic MILP model using the method proposed by Quesada and Grossmann (1995), then the stochastic MILP model is converted into its equivalent MILP deterministic model using the probabilistic theory. The fuzzy equivalent MILP model is converted to its crisp MILP model using the method proposed by Liu and Iwamura (1998). They solve the last two models using the branch-and-bound method. Both models are applied to large-scale refinery case study (267 continuous variables, 68 binary variables, and 320 constraints). They show that the chance-constrained method leads to slightly better performance, comparing with the fuzzy programming.

However, converting the chance-constrained models to their equivalent deterministic models is not an easy task due to the non-convexity of the feasible regions. Accordingly, different approximation methods are proposed such as sample average approximation (SAA) (Pagnoncelli, Ahmed, & Shapiro, 2009), sequential convex approximation (Hong, Yang, & Zhang, 2011), and kernel smoothing (Calfa, Grossmann, Agarwal, Bury, & Wassick, 2015).

Pagnoncelli *et al.* (2009) propose a method to approximate a joint portfolio chance-constrained problem with single constraint and random returns. Their proposed approach is based on replacing the actual probability distribution by an empirical distribution generated from random samples in order to evaluate the chance constrained. They conclude that small size samples lead to good performance. Hong *et al.* (2011) propose a sequential convex approximation algorithm to solve the stochastic chance-constrained problem. Their algorithm is a scenario-based, in which for each scenario, the sequential convex approximation model is solved using a gradient-based Monte-Carlo. However, such a scenario-based method needs high computational time to find the optimal, especially for large-scale industrial problems. Calfa *et al.* (2015) reformulate the data-driven chanced-constrained into algebraic constraints. They approximate the unknown true continuous probability density and distribution functions using kernel smoothing, so they can construct the confidence set based on the reformulated distribution function. However, such a method requires a large number of data in order to obtain efficient approximation.

iii) Fuzzy programming

The fuzzy programming method (Bellman & Zadeh, 1970) deals with the uncertain sources as fuzzy numbers and the uncertain constraints as fuzzy sets. A fuzzy number refers to a set of possible values.

Fuzzy optimization has many PSE applications. Peidro, Mula, Jiménez, and Botella (2010) propose a fuzzy linear programming tactical model for a multi-echelon multi-period automobile SC under uncertain fuzzy demand and supply. Aviso, Tan, and Culaba (2010) develop a fuzzy programming design model of water and wastewater reuse decentralized SC under uncertainty. The authors weight the effect of the network total benefit on the individual firms goals through fuzzy programming. Ng, Chemmangattuvalappil, and Ng (2015) propose a systematic fuzzy programming model for the optimal design of chemical product molecules considering robustness. They represent the robustness by the standard deviation between the experimental data and the estimated data resulted from the prediction model.

For MOO, Kasivisvanathan, Ng, Tay, and Ng (2012) propose a MOO fuzzy programming model to palm oil mills SCs producing crude palm oil. A degree of satisfaction is developed to analyze the multiple objective functions (environmental, economic) based on reliability. The fuzzy goals are predefined as the upper and lower bounds of the multiple objective functions. Mirhedayatian, Azadi, and Saen (2014) use the fuzzy programming for the evaluation of green production SC with dual-role factors, undesirable outputs and fuzzy data. They consider the inputs (RM acquisition, R&D, distribution, quality, advertisement, and reliability costs), outputs (production levels, flexibility of supplier, satisfaction, services), and dual-role factors as fuzzy triangular numbers. The outputs are considered as qualitative factors which are given a range between 1 and 5.

Comparing with the stochastic programming, Liu and Sahinidis (1996) show that the two-stage stochastic programming leads to better performance than the fuzzy programming, according to the context of process planning.

Combining the fuzzy programing with other approaches, Zhang *et al.* (2011) combine the fuzzy programming, the scatter evolutionary algorithm, and stochastic programming methods in one approach to optimize the tactical decisions of multi-echelon automobile SC under the demand and price uncertainties. Nie, Huang, Li, and Liu (2014) propose a multi-stage chance-constrained fuzzy dynamic programming approach for the strategic-tactical planning of energy SC under uncertainty. They evaluate the reliability of satisfying the system constraints as well as the risk of not satisfying them under different uncertain scenarios. Kundu, Kar, and Maiti (2014) develop a chance-constrained model with fuzzy parameters for two fixed-charge transportation problems.

iv) Robust optimization

Robust optimization (Ben-Tal, El-Ghaoui, & Nemirovski, 2009) aims to optimize the problem for the worst-case scenario by describing a deterministic equivalent "counterpart" of an uncertainty set that is feasible for all uncertainty events. Eq. (3.12) illustrates a simple robust optimization problem: $u \in U$ and A correspond to the uncertain values and the robust counterpart, respectively.

$$max_{x \in X} Z(x) : A(u, x) \leq b, \qquad \forall u \in U \tag{3.12}$$

Robust optimization has many applications to short-term problems. Bertsimas and Sim (2003) propose a computationally tractable robust integer programming to address data uncertainty for network flows problems. Their approach allows to control the degree of conservatism in function of the probabilistic bounds on constraint violation by restricting the uncertain parameters that take their worst-case values. Lin *et al.* (2004) propose a robust optimization model for continuous-time scheduling under the uncertainty of the processing times, demands, and prices. The model bounds the uncertain parameters between lower and upper bounds. Later on, this work has been extended by Janak, Lin, and Floudas (2007) to incorporate the probability distribution of the uncertain parameters.

Li and Li (2015) propose a robust optimization approximation to solve a chance-constrained model for a planning-scheduling problem. Their solution algorithm is divided into two steps: first, identifying the maximum set size that leads to feasible solutions, second, reducing this size to reliable solutions with best probability of constraint satisfaction (predefined reliability). After analyzing the relation between the uncertainty set size and reliability, the authors conclude that the reliability does not have to be monotonically related to the uncertainty set size. Later on, Yuan, Li, and Huang (2016) consider the correlation between the uncertain parameters when developing the robust optimization models.

Robust optimization methods prove to be more tractable comparing with their stochastic programing counterpart (Li *et al.*, 2011). However, recourse actions (reactions to uncertainty events) are not included in the robust optimization methods, thus limiting their applications to short-term problems (Zhang, Grossmann, Heuberger, Sundaramoorthy, & Pinto, 2015; Grossmann *et al.*, 2016). Accordingly, adjustable robust optimization techniques are proposed to account recourse actions for many PSE problems such as: inventory management (Ben-Tal, Goryashko, Guslitzer, & Nemirovski, 2004), logistics planning (Ben-Tal, Chung, Mandala, & Yao, 2011), operational planning (Verderame & Floudas, 2009), and process scheduling (Li & Ierapetritou, 2008; Zhang, Lima, & Grossmann, 2016b).

3.7.3 Monte-Carlo sampling

Monte-Carlo sampling method is based on repeated random sampling of uncertain parameters. It is also used to calculate the regression confidence of a sample to predict the model performance under different random scenarios. Monte-Carlo sampling method has many PSE applications such as: experimental modeling, simulation, optimization, regression, probability distribution and risk analysis, fault diagnosis, etc.

Jung, Blau, Pekny, Reklaitis, and Eversdyk (2004) use the Monte-Carlo sampling method to generate random set of safety stock scenarios in order to accommodate the demand uncertainty in the SC planning-scheduling optimization model. The required safety stock levels are obtained to maintain the customer satisfaction under different uncertain scenarios. Sin, Meyer, and Gernaey (2010) use the Monte-Carlo sampling method to predict the behavior of the cellulose hydrolysis under different uncertain parameters based on experimental data.

For pharmaceutical applications, Eberle, Sugiyama, and Schmidt (2014) implement the Monte-Carlo sampling method to improve the lead time of pharmaceutical batch production processes. The use of Monte-Carlo sampling method is to predict the future total lead-time and to obtain the summation of the probability distribution of each lead-time.

Monte-Carlo sampling method is also used to emulate non-linear complex models as in the work of Lambert, Rivotti, and Pistikopoulos (2013), who propose a Monte-Carlo-based approximation technique to approximate non-linear dynamic systems in order to apply linear-model predictive control (MPC) algorithms. The linearization process is based on generating N-step-ahead affine algebraic representations based on the conditional variances of the original mathematical model. This can be done by manipulating different variables using Monte-Carlo sampling method.

The use of Monte-Carlo sampling method as part of the optimization procedure is a practical way in reducing the complexity of the model formulation. In this thesis, Monte-Carlo sampling method is used to generate a high number of scenarios for the uncertain parameters. The use of Monte-Carlo sampling method in this thesis helps in obtaining the individual expected performance of the enterprises SCs participating in large-scale decentralized network. This also leads to obtain the probability distribution curves of the enterprises expected revenues to help decision-makers evaluating the different coordination contracts proposed in this document.

3.7.4 Financial risk management

The expected decisions resulted from the preventive approaches cannot hedge extreme uncertain events. So, efficient risk management is paramount in order to avoid any future disruptions. The trade-off between the risk metrics and the revenues must be considered in the optimization process.

Different risk metrics have been proposed in PSE literature such as variability index (Ahmed & Sahinidis, 1998); risk premium (Applequist, Pekny, & Reklaitis, 2000); variance (Gupta & Maranas, 2003); probabilistic financial risk (Barbaro & Bagajewicz, 2004; You *et al.*, 2009); downside risk (Eppen, Martin, & Schrage, 1989; Cheng *et al.*, 2003); value at risk (VaR) and conditional value at risk (Gebreslassie *et al.*, 2012; Zhang *et al.*, 2016a).

Ahmed and Sahinidis (1998) propose a variability index as a robustness measure to represent the variability of the second-stage costs for a 2-SSP process design and operation model. Their framework is based on penalizing the second-stage costs that are above the expected cost.

Applequist *et al.* (2000) present a risk premium metric as an objective function besides the the expected NPV within the context of SC MOO stochastic strategic-tactical model under demand uncertainty. Their risk premium metric is calculated as a function of the relation between the expected NPV and variance. They find out that the expected revenues vary linearly with the variance.

Gupta and Maranas (2003) also analyze the variability of the expected costs scenarios through the variance. They assume a variance target as a constraint, where the variance of the probability distribution of the cost must be less or equal this target. Their model is optimized as a multi-stage stochastic program considering the uncertainty of demand and a risk-neutral decision-maker. However, representing the variability of the expected performance using the variance may not be optimal, as they deal equally with the extreme events around the mean.

The downside-risk, first proposed by Eppen *et al.* (1989) is also considered as a financial risk metric. Cheng *et al.* (2003) consider the downside risk as an additional objective function besides maximizing the revenues and minimizing the process lifetime under the uncertainty of demand and technology evolution. They deal with the problem as a multi-period MOO Markov decision process with recourse, in which a 2SSP is solved each timespan. A set of solutions is obtained as a Pareto frontier. Later on, Barbaro and Bagajewicz (2004) manage the risk in a similar way, by identifying a cost target while minimizing the downside risk besides maximizing the expected NPV for a capacity expansion problem in the framework of two-stage stochastic programming.

Gebreslassie *et al.* (2012) analyze the conditional value at risk (CVaR) and downside risk as additional objective functions besides the expected revenues for the strategic design of hydrocarbon bio-refinery SC subjected to uncertainty of hydrocarbon biofuel demand and biomass supply. In order to reduce the computational time efforts, the authors implement the decomposition technique based on the Multi-cut Benders decomposition algorithm developed by You and Grossmann (2013). Later on, Zhang *et al.* (2016a) incorporate the CVaR as a financial risk metric in the stochastic operational model of power-intensive plants under the uncertainty of electricity price and product demand. According to the context of their work, the authors conclude that considering risk-averse approach leads to better solutions than the risk-neutral approach.

Different risk measures have been analyzed and compared. You *et al.* (2009)

analyze different risk measures (variance, variability index, downside risk, probabilistic financial risk) for a SC tactical problem under uncertainty of demand and freight rates. According to the context of their study, they conclude that the probabilistic financial risk and the downside risk lead to better performance. Later on, Cardoso *et al.* (2016) integrate four risk measures for the strategic-tactical MOO optimization of closed-loop SCs: variance, variability index, downside risk and CVaR. They conclude that the selection of the risk-measure depends on the risk behavior of the decision-maker; variability index is the most adequate for risk-averse decision makers, while the CVaR is the most adequate for risk-seeking decision makers.

However, the financial risk metrics depend on the firm preference. In this thesis, different solutions are proposed according to the enterprises decision-makers preferences and risk-behavior. Another metric is developed in this thesis to evaluate the variability of the performance metric scenarios based on the probability of acceptance. Furthermore, the effect of the uncertain behavior of the external partners (third parties) on the different risk behavior decision-makers is also analyzed in this thesis.

3.8 Modeling systems

Several commercial systems can be used to implement the mathematical models (deterministic, stochastic, etc.) such as the General Algebraic Modeling System (GAMS), the Advanced Integrated Multidimensional Modeling Software (AIMMS), A Mathematical Programming Language (AMPL), and the Open Programming Language (OPL). These modeling systems are connected automatically with several optimization solvers. They also have the ability to interface with other database packages or programs.

In this thesis, the GAMS modeling system is used to implement the developed mathematical models.

Part II

Global Coordination

Chapter 4

Global Coordination of Large-Scale Supply Chains with Third Parties

4.1 Introduction

Current Supply Chain (SC) tactical models focus on the optimization from a centralized perspective, disregarding the decisions of the supporting external enterprises "third parties" (raw materials and utilities suppliers, clients, waste and recovery systems, etc.). Third parties, which might face different enterprises (clients/providers), are represented by fixed parameters (price, capacity, etc.) in the decision-making process. By doing so, much information is lost leading to sub-optimal decisions, especially when a global coordination with a detailed master plan to be established in a competitive environment.

This chapter extends the tactical decision-making scope by including the detailed description of the third parties as full SC management problems. A global coordination framework is proposed to coordinate the decisions of the main production SC enterprises and their third parties within a global SC network with multiple echelons (main production SC and third parties SCs). A generic coordinated tactical model is developed to optimize the decision-making of multi-site multi-echelon multi-product global SCs under the objective function of minimizing the total cost of the whole system (main production SC cost plus the third parties SC cost), considering the production vs. demand coherence.

The advantages of the proposed generic model is illustrated using a case study which coordinates a multi-site multi echelon polystyrene production SC (as main enterprise) with a multi-site multi-echelon energy generation SC (as third party). The results show that the behavior of the third parties has a significant role in improving the global decision-making.

4.2 Problem statement and methodology

This chapter aims to optimize a global SC decision-making through coordinating the tactical decisions of all participants (main enterprise SC and third parties). The main enterprise multi-site multi-echelon multi-product SC consists of supplying, production, distribution, and storage echelons (Figure 4.1).

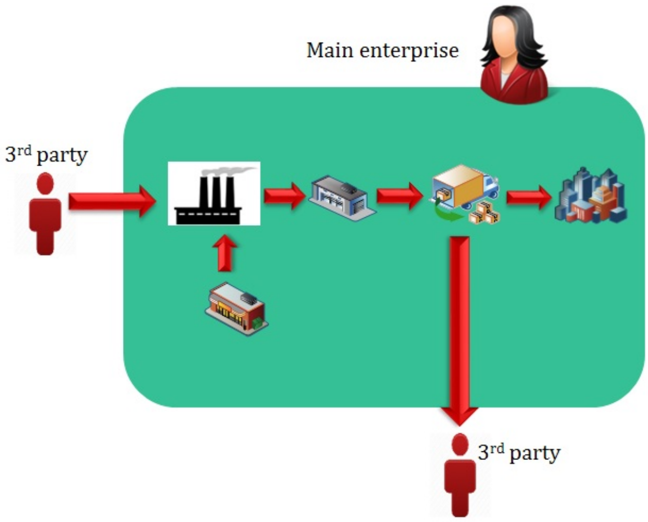


Figure 4.1: Main enterprise SC network

A global coordination approach is proposed based on incorporating the detailed information of the third parties as full SC management problem (Figure 4.2). The proposed approach is flexible enough to capture different simultaneous partitions; the resulted global SC network deals with the partitions SCs as echelons among the entire system. Within the coordinated framework, each echelon is able to, simultaneously, play different roles (e.g.: client in one SC, provider in another SC) according to the boundaries of the specific system to be optimized.

The resulting global SC is coordinated through the production vs. demand coherence among their production echelons. The main SC enterprise and the 3$^{\text{rd}}$ parties agree to collaborate towards optimizing the objective function of the whole system (summation of their objective functions).

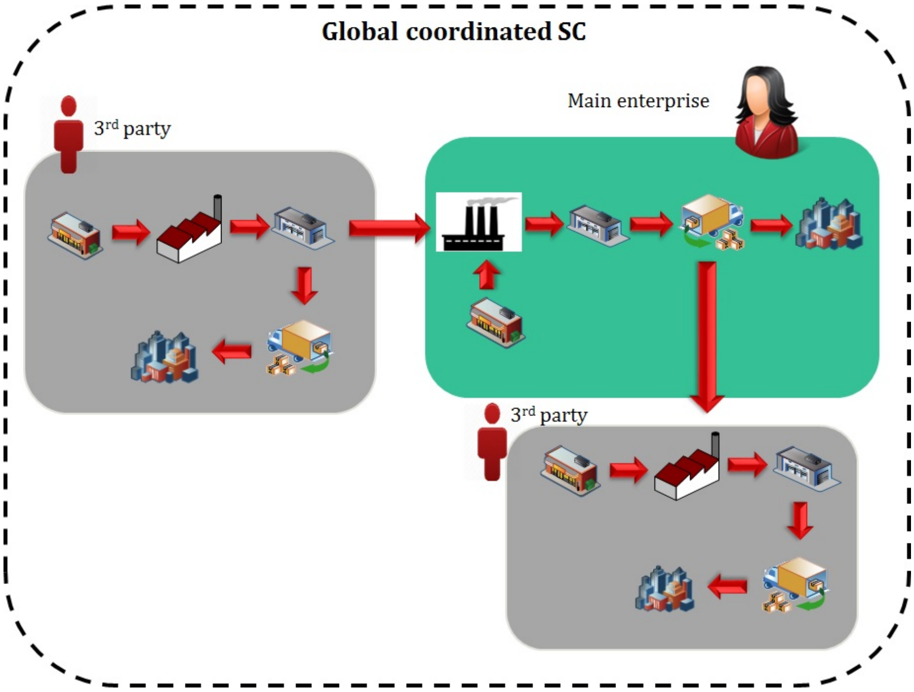


Figure 4.2: Global coordinated SC network

4.3 Mathematical formulation: a holistic model

A generic coordinated tactical model is developed, in which it integrates the detailed characteristics of the third parties as full SCs in the tactical decision-making process of multiple echelons. To do so, a set of echelons ($e1$, $e2$,...,E) is developed with their corresponding new subsets linking the elements (production plants/products/warehouses/markets) to their corresponding echelon. The proposed model also includes a set of external suppliers S and markets M. A set of resources R is developed to represent RM, intermediate/final products, energy, etc. Discrete time formulation is considered with a time horizon T. The coordinated model is built on several equality and inequality constraints representing the resources and economic balances, activities (production/storage/distribution) relations, and minimum/maximum capacities.

Eq. (4.1) represents the coordination between the production echelons of the SCs through the internal demand $InD_{r',e',t}$ vs. production between the supplying and production echelons.

$$InD_{r',e',t} = \sum_{r' \in R, r' \neq r} prf_{r,r',e}.PRD_{r',e,t} \qquad \forall r \in R; e \in E; e' \in E; t \in T \tag{4.1}$$

The final customer demand $dem_{r,e',t}$ of resource r must be satisfied from the SC echelons e (Eq. (4.2)). This equation can be easily modified to consider other policies such as penalty costs.

$$\sum_{e \in E, e \neq e'} DLV_{r,e,e',t} \geq dem_{r,e',t} \qquad \forall e' \in M; r \in R; t \in T \tag{4.2}$$

Eqs. (4.3), and (4.4) represent the minimum and maximum production, and storage capacities, respectively. No capacity constraints are considered for the external suppliers and the external markets, as they are out of the optimization boundary of the SC of interest.

$$prd^{min}_{r,e,t} \leq PRD_{r,e,t} \leq prd^{max}_{r,e,t} \qquad \forall r \in R; e \in E; t \in T \tag{4.3}$$

$$st^{min}_{r,e,t} \leq ST_{r,e,t} \leq st^{max}_{r,e,t} \qquad \forall r \in R; e \in (E - S - M); t \in T \tag{4.4}$$

Eq. (4.5) illustrates the resources balance, which must be satisfied at each echelon node. The resources stored at any time period in any echelon menus the safety stock menus the previously stored resources must be equal to the incoming resources menus the outgoing resources. The term $(prf_{r,r',e}.PRD_{r',e,t})$ represents the coordination among the several echelons, where the internal demand of the interacting resource r' (energy, wastewater, intermediate products, maintenance, etc.) is equal to the production levels of this resources in the provider SC echelon. This value depends on the utilized recipe represented by the production factor $prf_{r,r',e}$ using resources r, assuming linear correlation.

$$\begin{aligned} ST_{r,e,t} - st^{stock}_{r,e} - ST_{r,e,t-1} = &\sum_{e' \in E, e' \neq e} DLV_{r,e',e,t} + PRD_{r,e,t} \\ - \sum_{e'' \in E, e'' \neq e} DLV_{r,e,e'',t} - &\sum_{r' \in R, r \neq r'} prf_{r,r',e}.PRD_{r',e,t} \\ &\forall r \in R; e \in E; t \in T \end{aligned} \tag{4.5}$$

The objective function is to minimize the total cost of the global SC (Eq. (4.6)), which is the summation of the echelons SCs costs.

$$TCOST = \sum_{e \in E} COSt_e \tag{4.6}$$

Eq. (4.7) represents the cost of each echelon SC $COST_e$, which is equal to the summation of the external resources acquisition, production, storage and distribution costs, respectively.

$$COST_e = \sum_{t \in T} CRM_{e,t} + CPR_{e,t} + CST_{e,t} + CTR_{e,t} \tag{4.7}$$

The externally supplied resources acquisition cost $CRM_{e,t}$ is equal to the amount of external resources needed for the production processes multiplied by the unitary acquisition cost $urm_{r,e,t}$ for each echelon each time period (Eq. (4.8)). This equation can be extended when considering different pricing functions as in Chapter 5. The production cost $CPR_{e,t}$ is computed by considering the unitary production cost $upr_{r,e,t}$ of the resource r in echelon e (plants) each time period (Eq. (4.9)). The storage cost $CST_{e,t}$ (Eq. (4.10)) is obtained based on the amount of resources (RM, intermediate products, final products, etc.) stored each time period. Finally, the distribution cost $CTR_{e,t}$ is calculated based on the distance between the different echelons and the unitary transport cost, which depends on the product type, transport route, etc. (Eq. (4.11)).

$$CRM_{e,t} = \sum_{r \in R} P_{r,e,t}.Q_{r,e,t} \qquad \forall e \in E, t \in T \tag{4.8}$$

$$CPR_{e,t} = \sum_{r \in R} upr_{r,e,t}.PRD_{r,e,t} \qquad \forall e \in E, t \in T \tag{4.9}$$

$$CST_{e,t} = \sum_{r \in R} ust_{r,e,t}.ST_{r,e,t} \qquad \forall e \in E, t \in T \tag{4.10}$$

$$CTR_{e,t} = \sum_{r \in R} \sum_{e' \in E, e' \neq e} dis_{e,e'}.utr_{r,e,e'}.DLV_{r,e,e',t} \qquad \forall e \in E, t \in T \tag{4.11}$$

The total sales are computed based on the retailed price of the final product delivered to the external markets (Eq. (4.12)). Although, according to Eq. (4.2), additional delivery amounts to the external markets is allowed, its eventual revenues are not included, so this eventual mismatch between the delivering echelons and the external markets can be penalized, and the sales can be computed according to Eq. (4.13).

$$SALE_e = \sum_{r \in R} \sum_{e' \in M} \sum_{t \in T} rp_{r,e,t}.dem_{r,e,e',t} \qquad \forall e \in E \tag{4.12}$$

$$SALE_e = \sum_{r \in R} \sum_{e' \in M} \sum_{t \in T} \left[upl_{r,e,t}.dem_{r,e,e',t} + (rp_{r,e,t} - upl_{r,e,t}) \sum_{e' \in M} DLV_{r,e,e',t} \right] \quad \forall e \in E \tag{4.13}$$

Eq. (4.14) represents the total sales of the global SC, which is the summation of the echelons sales.

$$TSALE = \sum_{e \in E} SALE_e \tag{4.14}$$

Finally, the total SC profit (Eq. 4.15) is computed as the difference between the total sales and the total costs.

$$PROF = TSALE - TCOST \tag{4.15}$$

These mathematical formulations result in a LP tactical model, which is flexible enough to deal with the arising complexity due to the incorporation of different SCs with their detailed characteristics. The proposed model is generic enough to be applied to single echelon and large-scale multi-echelon SCs, depending on the boundary of the SC under study. Furthermore, the developed LP model can be easily extended to cope with the nonlinearities resulted from considering complex production recipes, cost functions, uncertainty (e.g: prices fluctuations, non-linear forecasted demands, resources availability, etc.). The proposed model also has room to consider discrete decisions such as assignment production and distribution elements, piecewise price functions, etc.

4.4 Case study

The advantages of the proposed model has been illustrated using a case study of a multi-site multi-echelon multi-product polystyrene production-distribution SC and a multi-site multi-echelon energy generation SC (Figure 4.3).

The polystyrene production SC consists of 4 raw materials suppliers ($sup1$, $sup2$, $sup3$, and $sup4$), 3 polystyrene production plants ($pl1$, $pl2$, and $pl3$), 2 distribution centers ($dc1$ and $dc2$), and 4 markets ($mk1$, $mk2$, $mk3$, and $mk4$). The polystyrene production SC produce 2 products (A and B) using $rm1$ and $rm2$ to produce product A, and $rm3$ and $rm4$ to produce product B. The polystyrene production SC receives energy from the energy generation SC. The SC includes a wastewater treatment plant (WWTP) with an energy rate of 0.43 kWh/ton.

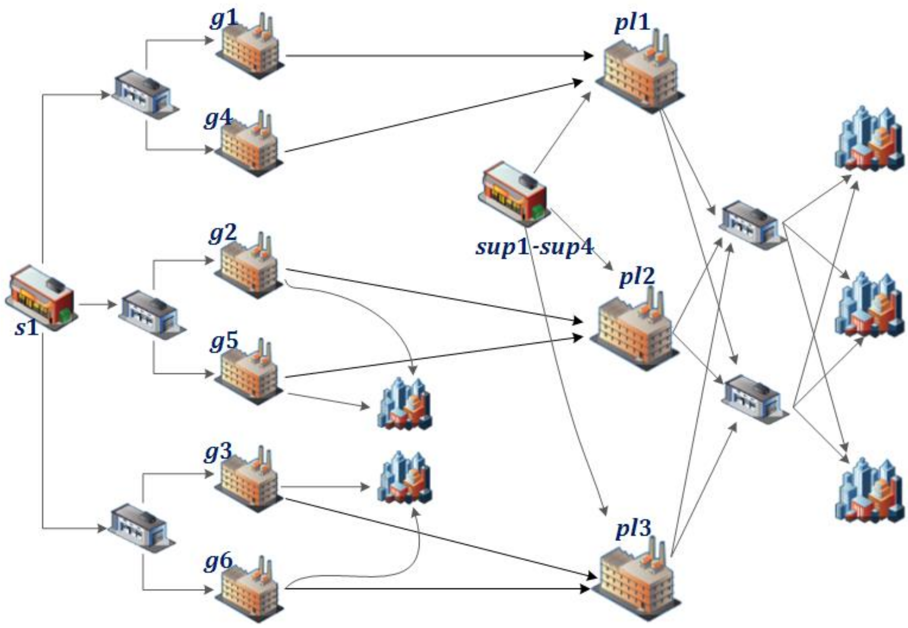


Figure 4.3: Global SC network

The energy generation SC includes one RM supplier of different biomass sources and coal (wood pellets-$b1$, coal- $b2$, petcock-$b3$, and marc waste-$b4$) feeding 6 renewable energy generation plants: 3 gasification plants ($g1$, $g2$, and $g3$) and 3 combustion plants ($g4$, $g5$, and $g6$). The energy generation SC has 200 kg safety stock of RM with a storage capacity of 1000 tons/time period. It is assumed that the RM transport and storage is on the charge of the SCs enterprises; no minimum capacities are considered for any of the SCs activities.

The characterization parameters of the whole system network are summarized in Tables (Appendix B.1-B.11).

The coordination approach regards the polystyrene production SC enterprise as the main enterprise, and the energy generation enterprise as the third party. This results in a global SC with multiple echelons (Figure 4.4).

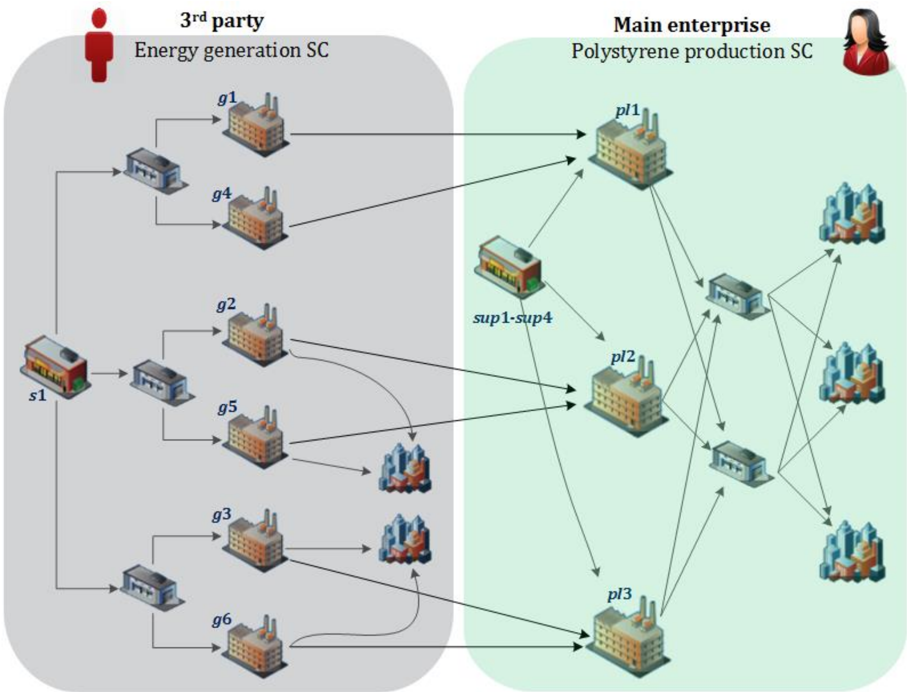


Figure 4.4: Coordinated global SC network

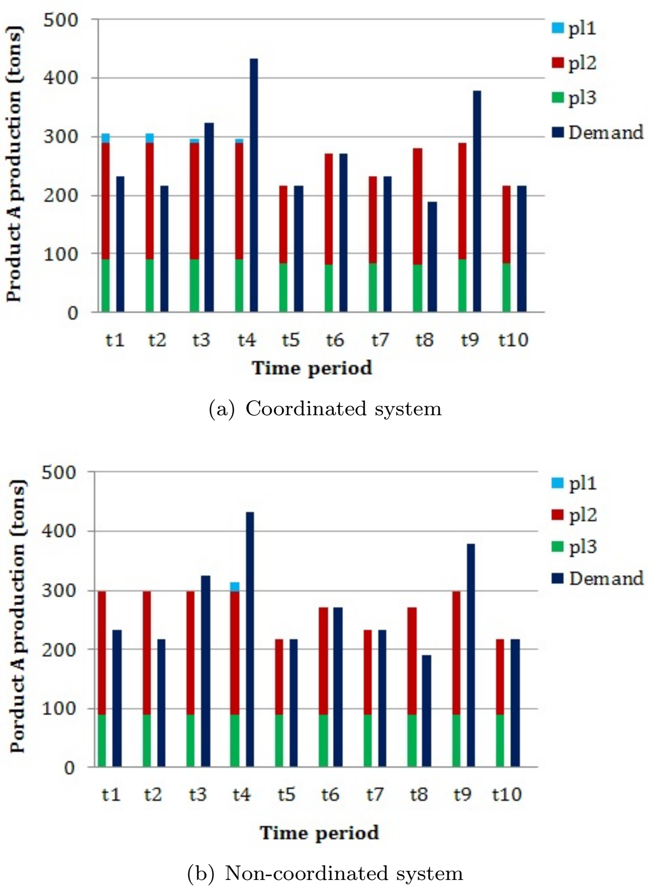
4.5 Results and discussion: coordinated vs. non-coordinated systems

The model formulations are implemented to GAMS and solved using CPLEX 12.50 to the above case study for 10 time periods; 1000 working hours each. The results of the proposed coordinated approach are analyzed and compared with the traditional non-coordinated approach. The coordinated approach results in one tactical model to be solved under the objective function of minimizing the total cost of the whole SC network. The non-coordinated approach results in two tactical models to be optimized, separately, under the objective function of minimizing the individual costs considering the interaction between the SCs (supply/demand) as fixed parameters.

4.5.1 Tactical decision-making

Then the optimal tactical decisions of the global SC are obtained. The results show that different tactical decisions are obtained for both polystyrene and energy SC enterprises. Figures 4.5 and 4.6 illustrate the polystyrene production levels of products A and B resulted from the cooperative coordinated and non-coordinated approaches. It is noticed that the polystyrene production orders resulted from the coordination system have been reallocated to reduce the load on the energy generation SC. For example, using the coordinated approach, to produce product A, the polystyrene production plant $pl1$ functions at the first time periods ($t1$-$t4$) to the high demands at $t4$, and the excess amounts will be stored and distributed later at $t4$.

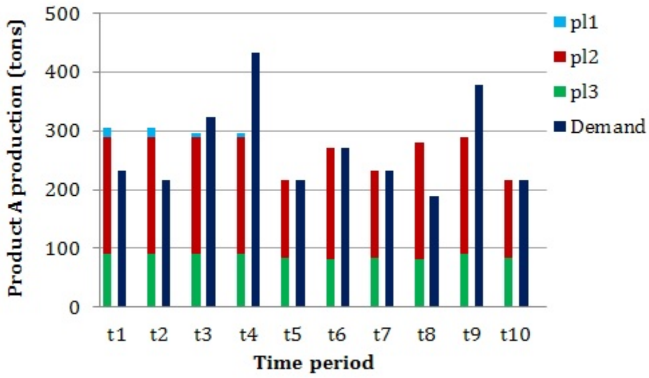
For the non-coordination system, the production plants $pl2$ and $pl3$ are overloaded up to their production capacities, while $pl1$ is shut all time periods except at $t4$ due to the high demand at this time period. This non-cooperative behavior forms a load pressure on the energy generation plants feeding $pl2$ and $pl3$ (see Figure 4.3). The dominance of the polystyrene production plant $pl2$ to produce product A is due to its closest distance to the dominant RM suppliers $sup2$ and $sup3$ (see Table Appendix B.10), while the polystyrene production plants $pl1$ and $pl3$ dominate producing product B.



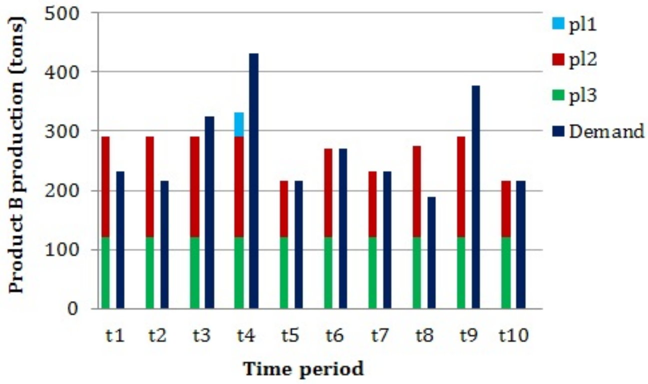
(a) Coordinated system

(b) Non-coordinated system

Figure 4.5: Polystyrene production levels (product A)



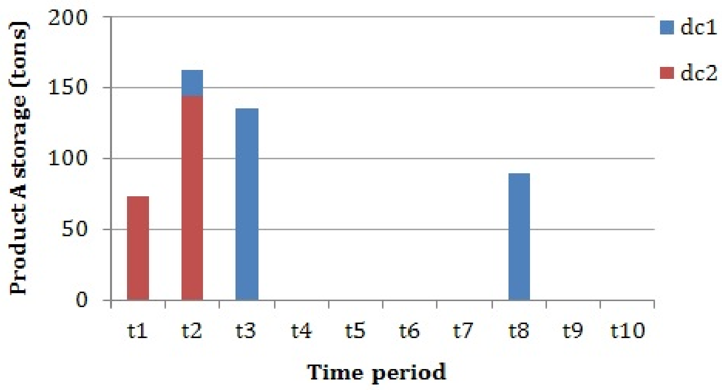
(a) Coordinated system



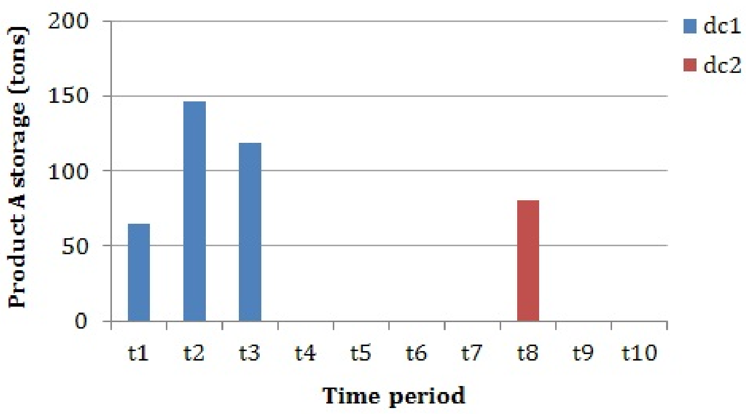
(b) Non-coordinated system

Figure 4.6: Polystyrene production levels (product B)

Consequently, the polystyrene storage levels (Figures 4.7 and 4.8) have been reallocated to follow the production levels (see Figures 4.5 and 4.6). For example, the storage levels are high at time periods $t1$-$t3$ and $t8$ to store the excess of the high production levels at those time periods, so to be distributed later at higher demand periods (i.e $t4$ and $t9$).

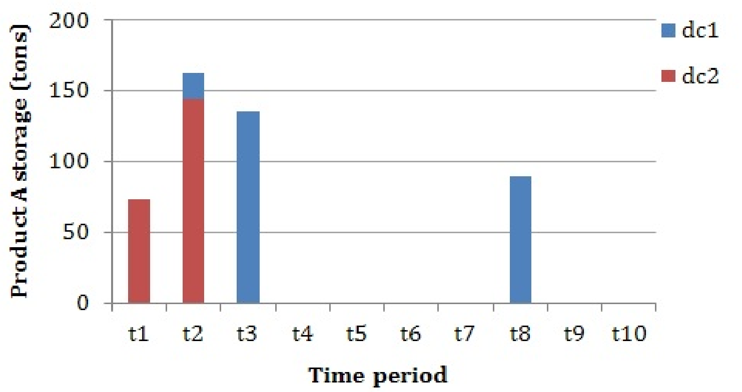


(a) Coordinated system

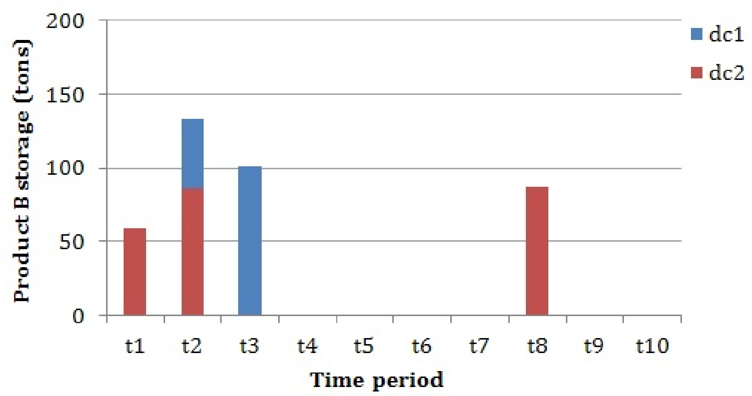


(b) Non-coordinated system

Figure 4.7: Polystyrene storage levels (product A)



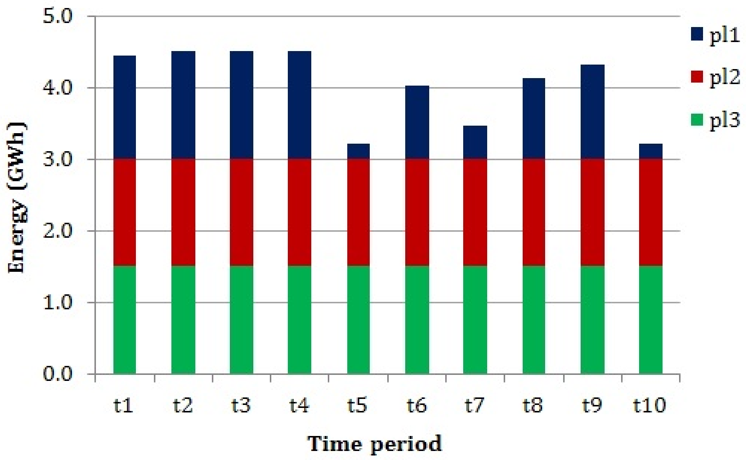
(a) Coordinated system



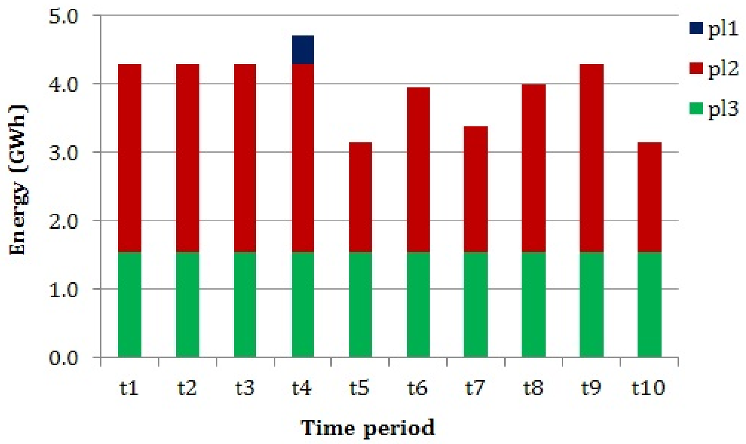
(b) Non-coordinated system

Figure 4.8: Polystyrene storage levels (product B)

Figure 4.9 shows the energy flows between the energy generation plants and the polystyrene production plants. Figure 4.9(a) illustrates the energy flows resulted from optimizing the coordinated SC model. Figure 4.9(b) shows the energy required for the polystyrene production resulted from solving the polystyrene production SC model, separately. These energy amounts are introduced as fixed energy demands for optimizing the energy SC tactical model, separately (non-coordinated). It is noticed that using the proposed coordinated approach results in less energy order loads resulting from functioning all the polystyrene production plants. This can be seen clearly in Figure 4.10.



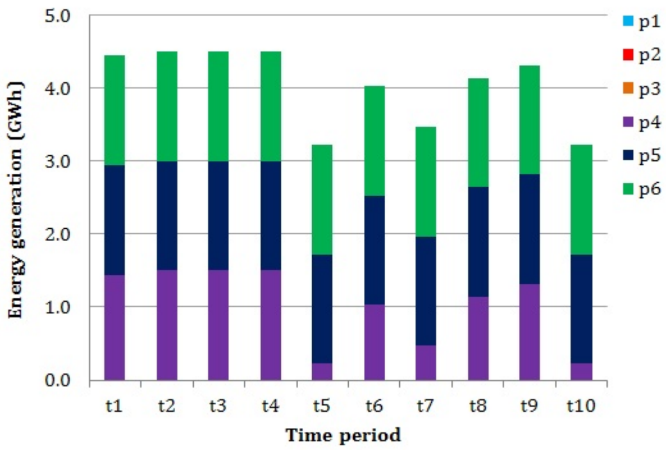
(a) Coordinated system



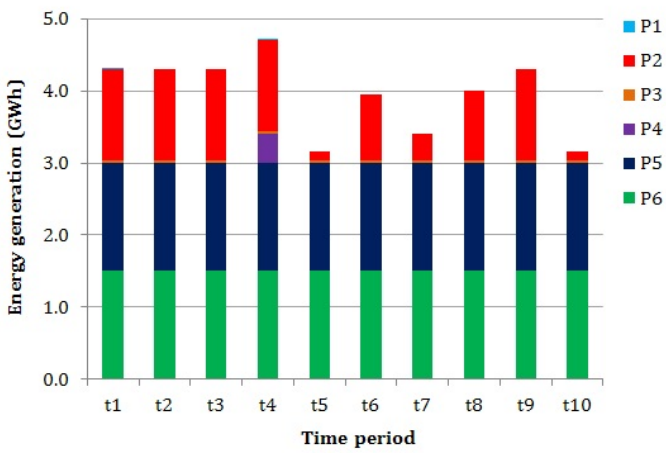
(b) Non-coordinated system

Figure 4.9: Energy flows (supplied/demanded)

The energy generation levels among the renewable energy plants can be seen in Figure 4.10. It is noticed that the energy generation levels follow the energy demands by the polystyrene plants as in Figure 4.9 and the energy external markets (see Table Appendix B.11). The trend of the coordinated system is to function the cheapest energy generation plants (combustion plants $g4$, $g5$ and $g6$), while the non-coordinated system leads to function the combustion plants $g5$ and $g6$ up to their generation capacity (5 GWh/time period) and the gasification plant $g2$ (expensive choice) in order to cover the rest of the energy demands.



(a) Coordinated system



(b) Non-coordinated system

Figure 4.10: Energy generation levels

Accordingly, using the non-coordinated system, the polystyrene SC enterprise decision-maker forms a pressure on the energy generation SC to generate energy according to her/his best conditions, leading to generate many energy plants up to their capacity. Such a bias situation may lead to infeasible solutions in case of higher energy demands than the energy generation capacity, and thus leads to disruptions in the whole system. This stresses the importance of the proposed coordinated approach, as it incorporates the detailed description of the energy generation SC to avoid infeasible and expensive solutions. Using the coordination approach leads to different SC behaviors, and thus affects the tactical decision-making of the whole system.

4.6 Economic analysis

As described in the above section, the coordination approach leads to flexible and feasible solutions for all participants. This section analyses the effect of the coordination approach on the total costs. Table 4.1 summarizes the economic results of both participating SCs, comparing with the non-coordinated system. It is noticed that the coordination leads to 2.5% savings in the total cost (434,170 m.u.) in 10 time periods.

Table 4.1: Economic analysis

	Non-coordinated SCs	Coordinated SCs
Echelon 1 (Energy SC) cost (10^3 m.u.)	7,373	6,894
Echelon 2 (Polystyrene SC) cost (10^3 m.u.)	10,745	10,790
Total cost (10^3 m.u.)	18,118	17,684

Figure 4.11 illustrates the economic breakdown of the total costs resulting from the coordinated system, in comparison with the non-coordinated system. It can be observed that coordinated SCs behave in favor of the global SC objective function. The distribution cost of the polystyrene production SC slightly increase by 2.3%, but, simultaneously, the energy generation SC improves the savings of the RM acquisition, distribution, and energy generation total costs by 4.9% (34,357 m.u.), 0.3% (1,584 m.u.), and 7.8% (442,974 m.u.), respectively. Although the coordination leads to slightly increase (0.42%) in the polystyrene production SC total cost, but, a high savings (6.95%) in the energy generation SC can be achieved. Consequently, a trade-off among the decisions of both SCs enterprises (main enterprise and the third party) can be seen.

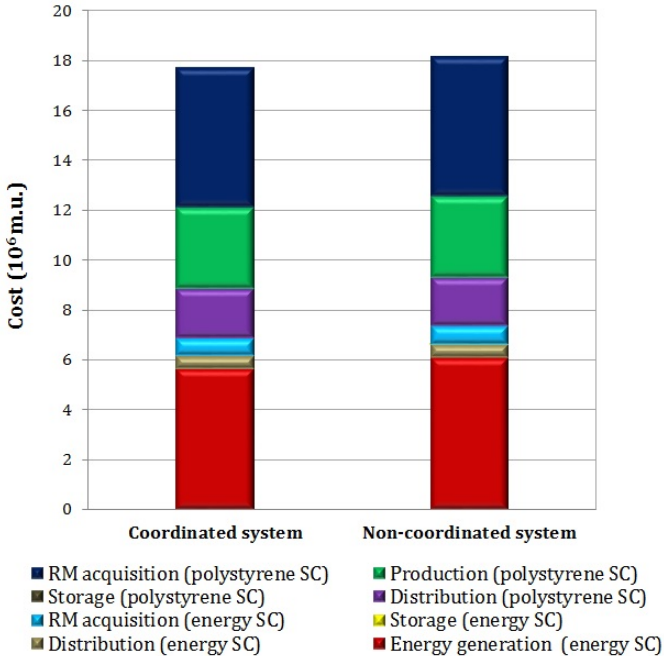


Figure 4.11: Total cost breakdown

4.7 Final considerations

In this chapter, a global coordination approach has been proposed and compared with the traditional non-coordinated approach. The tactical decisions of the SCs enterprises have been coordinated with their supporting external enterprises "third parties" (raw materials and utilities suppliers, clients, waste and recovery systems, etc.). A generic LP coordinated tactical model is presented considering the detailed description of the participants (main enterprises and third parties) as full multi-site multi-echelon multi-product SCs, flexibly linked together among a global SC network of multiple echelons.

The resulting coordinated tactical model is useful to analyze the behavior of the echelons SCs, which is found to be different than the non-coordinated system. Such a behavior affects the tactical decisions of both SCs, since the coordinated model allows to find better global behavior. Al these elements are incorporated in the proposed coordinated tactical model, which is able to optimize any multi-site multi-echelon multi-product SC problem, taking into consideration the detailed characteristics of each echelon/ organization interacting within one global SC network.

The proposed model allows coordinating the production, storage and distribution activities of all echelons, and thus it helps in improving the global objective of the whole system. All participants organizations decisions are affected by the decision-making of the whole system. This allows the participants organizations to share responsibilities. This work can be easily extended to incorporate uncertainty issues, so all participants can also share future risks.

The coordination approach has been tested and compared to a global multi-site multi-echelon multi-product SC with two interacting SCs (polystyrene production SC and renewable energy generation SC). The results show improvements in the total cost with less RM use, while meeting the same market requirements.

Finally, this chapter adds to PSE a new decision-support tool able to coordinate the information of all participants involved in system of study towards global objectives and optimal resource management.

Next chapter, this work will be extended to incorporate the decisions of the external competitive suppliers through optimal integration of their complex policies.

4.8 Nomenclature

Indices

e	echelon (production plant, distribution center, market,...)
r	resource (raw material, product, energy, steam, cash,...)
t	time period

Sets

E	echelons (production plant, distribution center, market...)
M	final customer
S	external suppliers
R	resource (raw material, product, energy, steam, cash,...)
T	time period

Parameters

$dis_{e,e'}$	distance between echelon e and echelon e'
$dem_{r,e,e',t}$	external demand of resource r at echelon e from echelon e' (final consumer), time t
$p_{r,e,t}$	unitary resource r cost from echelon e (supplier), time t
$prd^{max}_{r,e,t}$	maximum delivering capacity of resource r at echelon e (production plant/supplier), time t
$prd^{min}_{r,e,t}$	minimum delivering capacity of resource r at echelon e (production plant/supplier), time t
$prf_{r,r',e}$	production factor of resource r' from resource r in echelon e
$St^{stock}_{r,e}$	initial stock level of resource r in echelon e
$St^{max}_{r,e,t}$	maximum storage capacity in echelon e for resource r, time t
$St^{min}_{r,e,t}$	minimum storage capacity in echelon e for resource r, time t
$upr_{r,e,t}$	unitary production cost value to produce resource r from at echelon e, time t

$upl_{r,e,t}$	unitary penalty cost for extra-delivery of resource r at echelon e (market), time t
$ust_{r,e,t}$	unitary storage cost of resource r at echelon e, time t
$utr_{r,e,e'}$	unitary transport cost for resource r from echelon e to echelon e'
$rp_{r,e,t}$	retailed price of resource r at echelon e, time t

Variables

$COST_e$	cost of echelon e
$CPR_{e,t}$	production cost at echelon e, time t
$CRM_{e,t}$	externally supplied resources cost at echelon e, time t
$CST_{e,t}$	storage cost at echelon e, time t
$CTR_{e,t}$	transport cost at echelon e, time t
$DLV_{r,e',e,t}$	amount of resource r delivered from echelon e' to echelon e, time t
$InD_{r',e',t}$	internal demand of resource r' from echelon e', time t
$PRD_{r',e,t}$	production levels of resource r' in echelon (plant) e, time t
$PROF$	total profit
$Q_{r,e,t}$	resources r purchased from external suppliers at echelon e, time t
$SALE_e$	sales of echelon e
$ST_{r,e,t}$	storage level of resource r in echelon e, time t
$TCOST$	total cost
$TSALE$	total sales

Chapter 5

Optimal Integration of Competitive Third Parties

5.1 Introduction

The competitiveness among chemical industry SCs enterprises stresses the necessity of effective coexistence between them through global coordination considering their supporting enterprises (third parties) (resource suppliers, clients, waste & recovery systems, etc.). In the reviewed literature, the relationships between third parties and their clients/providers are characterized by simple economic transactions represented by fixed parameters, and they are usually modeled by average prices. The pricing behavior of the third parties resources is usually neglected, which may affect the SC equilibrium.

Since demand is a price sensitive (Viswanathan & Wang, 2003), prices can be considered as a driving force for effective decision-making. So, incorporating the pricing decisions of the third parties with some discounts can be considered as joint collaboration tool to capture competitiveness. The prices polices of the third parties, as dynamic marketing variables, affect the supply/demand orders, and thus any pricing decision will affect the global coordination of the whole network under study. None of the reviewed literature integrate the third parties prices policies as part of the decision-making process of global interacting SCs. By doing so, the impact of the third parties on the decision-making of the business partners and vice versa is neglected, leading to sub-optimal decisions from the global point of view, especially in a highly competitive environment. Accordingly, integrating the third parties decisions and policies in the global coordinated SCs decision-making becomes a challenging problem as enterprises seek competitive performance, especially when their coordination is highly affected by the competitive behavior of their third parties.

In this chapter, the global coordination framework proposed in Chapter 4 is extended to integrate the resources and financial flows of the surrounding third parties based on the trade-off between the third parties marketing and the coordinated SC operations. The global coordinated SC boundary is extended to incorporate the price polices of the competitive third parties, thus enabling them a degree of freedom to control their financial nodes with the global coordinated SC. A generic tactical coordinated base model is developed integrating the decisions of the competitive third parties and prices policies as part of the decision-making process of multi-echelon multi-product coordinated SC.

Then, to achieve a more realistic evaluation of those prices policies in each marketing situation, different pricing approximation models are proposed and compared to estimate the price policy of each third party. The pricing approximation models are developed based on fixed, piecewise, and polynomial price vs. demand relationships. The piecewise and polynomial pricing approximation models are built on prices discounts based on price elasticity of demand, so the third parties can compete in the global market. The use of different price approximation functions results in LP, NLP, and MINLP tactical optimization models aiming to minimize the global coordinated SC cost. The effects of using the proposed models on the global SCs coordination are verified and compared using the case study extended from Chapter 4. The results show that the pricing approximation type affects the individual and global SCs tactical decision-making, with the worst decisions regarding the use of average pricing approximation.

5.2 Problem statement and methodology

The objective of this chapter is to achieve global coordination considering the dynamic interaction among the participating enterprises and their competitive third parties in a multi-site multi-echelon multi-product SC (Figure 5.1). The coordination framework proposed in Chapter 4 is extended to include the third parties decisions in the global SC tactical decision-making process. The global SC consists of a production SC echelon and a provider SC echelons, all of them are surrounded by different competitive third parties. The main production SC produces products to final customers using resources (RM, intermediate products,etc.) from the provider SC and third parties. The provider production SC delivers products to final customers and to the production SC using resources from third parties. The main partners of collaboration are the global coordinated decision-maker and the third parties.

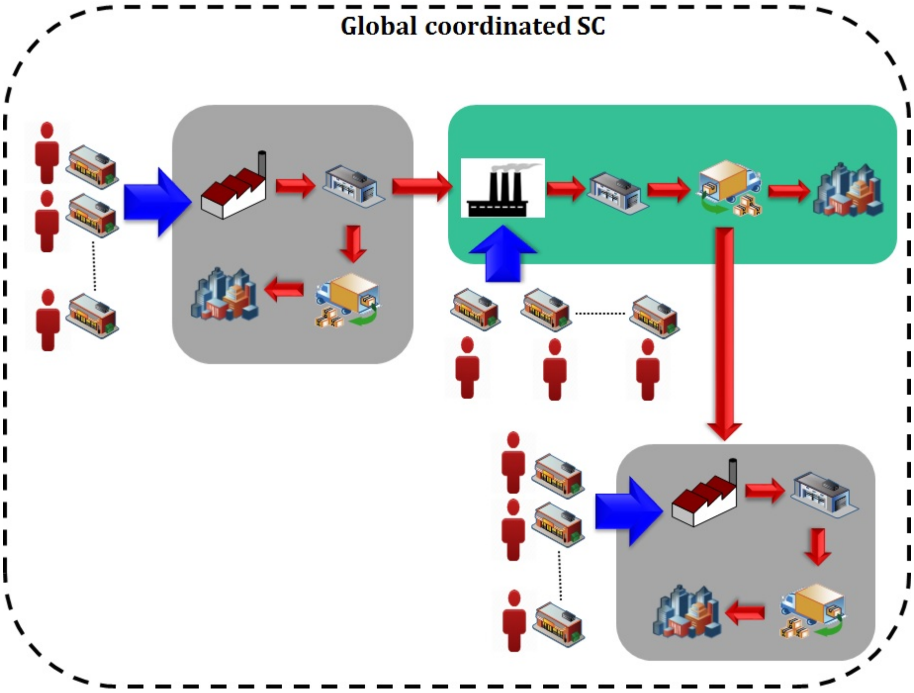


Figure 5.1: Coordinated global SC network

Each participating third party has its own real price policy in function of the quantity demanded by the global coordinated SC decision-maker (Figure 5.2). These real price polices will be incorporated into the global tactical model as a joint collaboration tool between the global coordinated SC decision-maker and all competitive third parties. Such polices are complex to integrate into the model formulation, so, and in order to be more realistic, different pricing approximation models are developed based on average fixed, piecewise, and polynomial functions to estimate the real prices policies of all third parties. The participating enterprises cooperative in one global coordinated network, taking into consideration their detailed information and the price policies of their competitive third parties. All of them collaborate to enhance the global coordination that satisfies the markets demands under the summation of their objective functions.

Figure 5.2: 3^{rd} party real price policy

5.3 Mathematical formulations

The generic coordinated tactical model proposed in Chapter 4 is conveniently modified and extended for the purpose of this chapter. The main objective of the proposed coordinated tactical model is to achieve the global coordination with all participants through synchronizing their activities taking into consideration their detailed characteristics as full SCs with their competitive third parties. This can be done by integrating the trade-off between the third parties prices and quantity demanded (Eq. (5.1)). As first step, the prices of the third parties resources are considered as degree of freedom decisions in the tactical base model. Then, this base model is extended to test the different pricing approximations. To do so, a set echelons ($e' \in D$) is proposed to represent the third parties in the model formulations.

Eq. (4.8) in Chapter 4 is extended to include the unit resource price $P_{r,e',t}$ as decision variable among the global coordinated model (Eq. (5.1))

$$CRM_{e,t} = \sum_{e' \in D, e' \neq E} \sum_{r \in R} P_{r,e',t}.Q_{r,e',e,t} \qquad \forall e \in E; t \in T \tag{5.1}$$

Then, the generic base model is divided into several tactical pricing models according to the pricing approximation approach, as explained in the next subsections:

5.3.1 Average fixed pricing model

The real price policy of each third party is approximated to an average fixed price vs. quantity demanded. In this case, the quantity demanded is considered perfectly elastic over the time horizon t (Figure 5.3).

Eq. (5.2) illustrates the price $P_{r,e',t}$ function considering average fixed approximation.

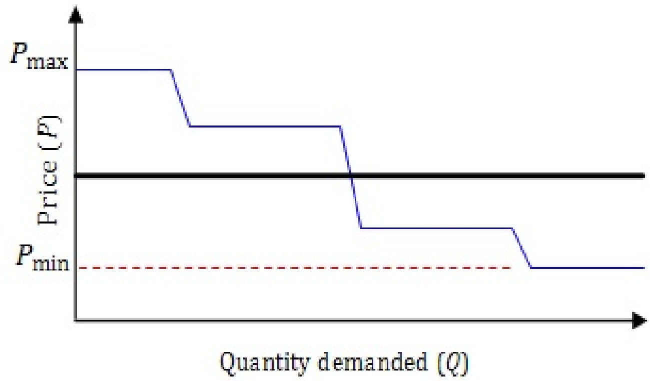


Figure 5.3: Fixed pricing vs. demand

$$P_{r,e',t} = \sum_{r \in R} (Pf^{max}_{r,e',t} + Pf^{min}_{r,e',t})/2) \qquad \forall e' \in D; e' \in E; e' \neq E; t \in T \quad (5.2)$$

5.3.2 Polynomial pricing model

Based on the price elasticity of demand, a polynomial pattern is adjusted (Figure 5.4). The price of the external resources $P_{r,e',t}$ can be calculated as in Eq. (5.3), where $c_{a,r}$ is a parameter depending on the initial price, resource capacity, and price elasticity of demand.

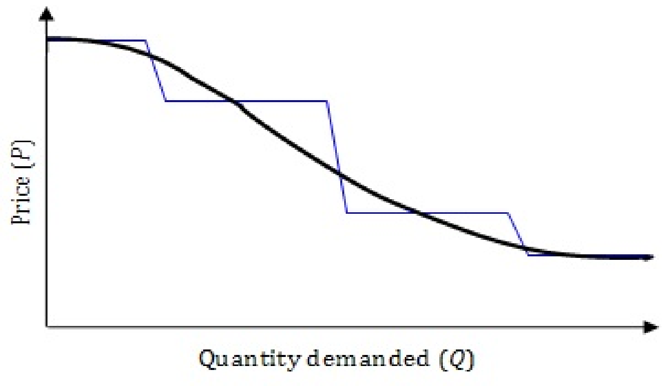


Figure 5.4: Polynomial pricing vs. demand

$$P_{r,e',t} = \sum_{a=1}^{A} c_{a,r}.(Q_{r,e',e,t})^{A-a} \qquad \forall r \in R; e' \in D, e \in E; e' \neq E; t \in T \quad (5.3)$$

Different polynomial grades can be implemented using Eq. (5.3), depending on the polynomial grade function represented by A.

5.3.3 Piecewise pricing model

The piecewise pricing model is based on assigning different prices to the quantity demanded per time. several pricing zones ($n = 1, 2, ..., N$) are defined by each third party depending on the quantity demanded $Q_{r,e',e,t}$ along the time horizon T (Figure 5.5).

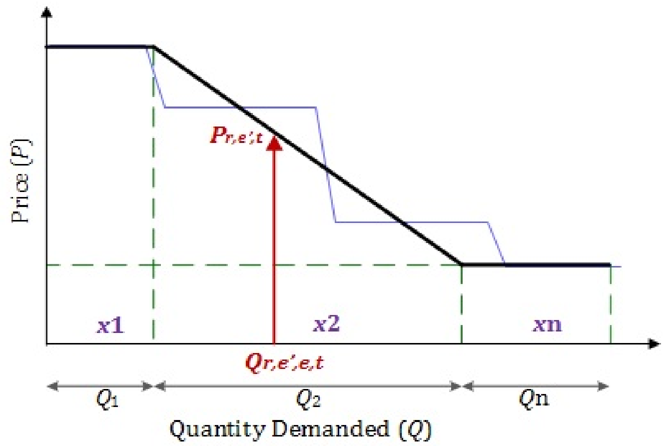


Figure 5.5: Piecewise pricing vs. demand

To allocate each quantity to its corresponding price, binary variables ($x1$, $x2$,...,xn) (Eq. (5.4)) are used.

$$\sum_{n \in N} x_{r,e',t,n} \leq 1 \qquad \forall r \in R; e' \in D; e \in E; e' \neq e; t \in T \tag{5.4}$$

The resources quantities constraints each pricing zone are identified as in Eq. (5.5).

$$x_{r,e',t,n} \cdot Q^{max}_{r,e',e,t,n-1} \leq Qn_{r,e',e,t,n} \leq x_{r,e',t,n} \cdot Q^{max}_{r,e',e,t,n}$$
$$\forall r \in R; e' \in D; e \in E; e' \neq e; n \in N; t \in T \tag{5.5}$$

It is assumed that the quantity demanded $Q_{r,e',e,t}$ from each third party can be ordered once at any time period. This means that $Q_{r,e',e,t}$ is equal to $Q1$, or $Q2$, (...), or Qn (Eq. (5.6)).

$$Q_{r,e',e,t} = \sum_{n \in N} Qn_{r,e',e,t,n} \qquad \forall r \in R; e' \in D; e \in E; e' \neq e; t \in T \tag{5.6}$$

The price elasticity of demand $ED_{r,e',t,n}$ is calculated as in Eq. (5.7).

$$ED_{r,e',e,t,n} = \frac{\delta Qn_{r,e',e,t,n}}{\delta Pn_{r,e',t,n}} \qquad \forall r \in R; e' \in D; e \in E; n \in N; t \in T \tag{5.7}$$

The external resource price $Pn_{r,e',t,n}$ each pricing zone is identified as in Eq. (5.8), where $P^{max}_{r,e',t,n}$ corresponds to the price limit of any pricing zone $n \in N$.

$$x_{r,e',t,n}.P^{max}_{r,e',t,n} \leq Pn_{r,e',t,n} \leq x_{r,e',t,n}.P^{max}_{r,e',t,n} \qquad \forall r \in R; e' \in D; n \in N; t \in T \tag{5.8}$$

Then the third parties resources prices $P_{r,e',t}$ is calculated as in Eq. (5.9)

$$P_{r,e',t} = \sum_{n \in N} Pn_{r,e',t,n} \qquad \forall r \in R; e' \in D; t \in T \tag{5.9}$$

The above mathematical formulations result in LP (fixed pricing model), NLP (polynomial pricing model), and MINLP (piecewise pricing model) programs. These programs are solved to minimize the total cost of the global coordinated SC. The tactical master plan is to be obtained over the resources acquisition from third parties, unit transfer price, production, storage, and distribution flows and directions along a discrete time horizon T.

5.4 Case study

The impact of using the proposed LP/NLP/MINLP pricing approximation models on the individual and global decision-making is demonstrated using a case study modified and extended from chapter 4 (Section 4.4). Four biomass and coal suppliers compete as third parties to provide resources ($b1$, $b2$, $b3$, and $b4$) to the energy generation SC (Figure 5.6).

On the other side, four suppliers compete as third parties to sell 4 types of RMs ($rm1$, $rm2$, $rm3$, and $rm4$) to the polystyrene production SC. The main purpose is to determine the resources physical/economic flows (blue lines in the figure) between third parties and the global SC along the considered planning horizon that guarantee optimal coordination among all participants.

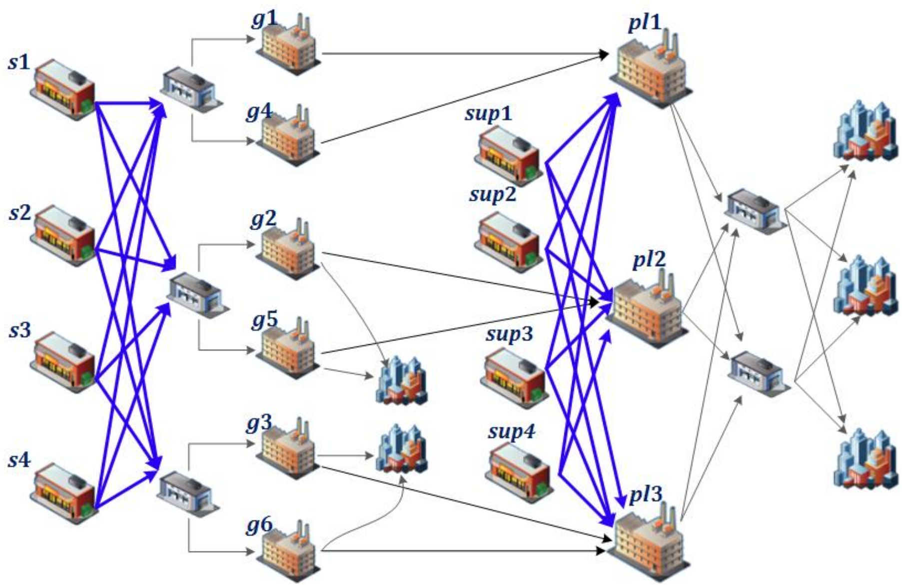
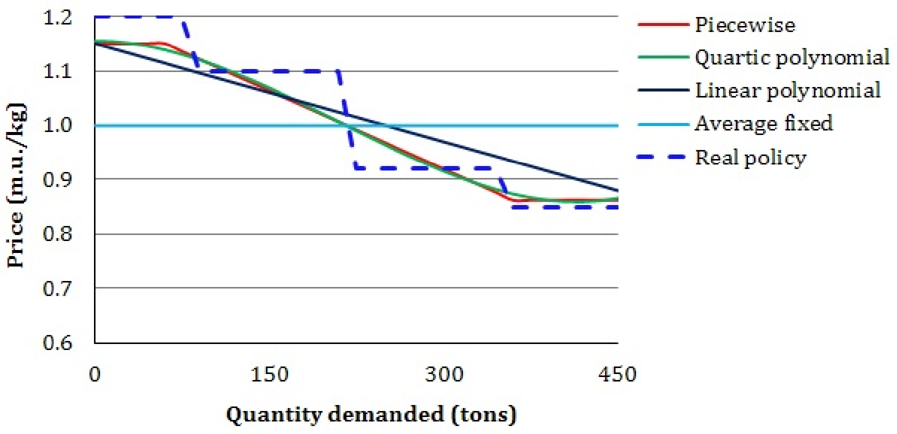


Figure 5.6: Case study

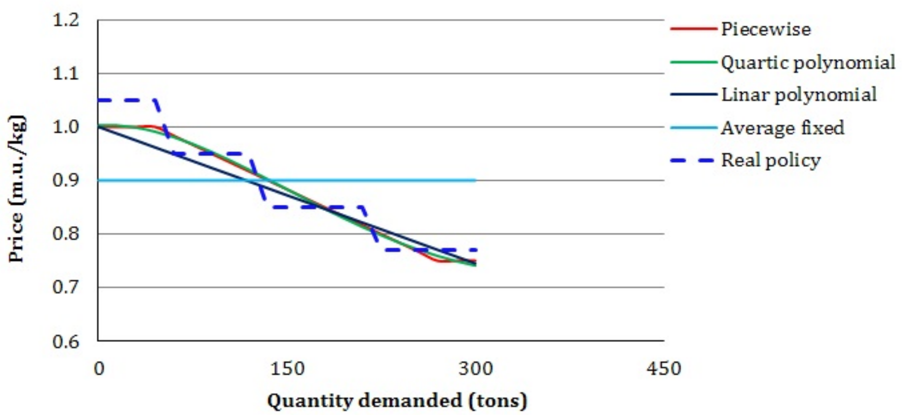
5.4.1 Pricing models implementation

The third parties price policies have been assumed arbitrarily, based on their current market prices range, along the considered planning time horizon. Each competitive third party has its own price policy. Then, these complex price policies are approximated resulting in four pricing approximation models: i) average fixed, ii) piecewise, iii) quartic polynomial, and iv) linear polynomial (Figures 5.7 and 5.8), to be used during the optimization process of the coordinated global SC.



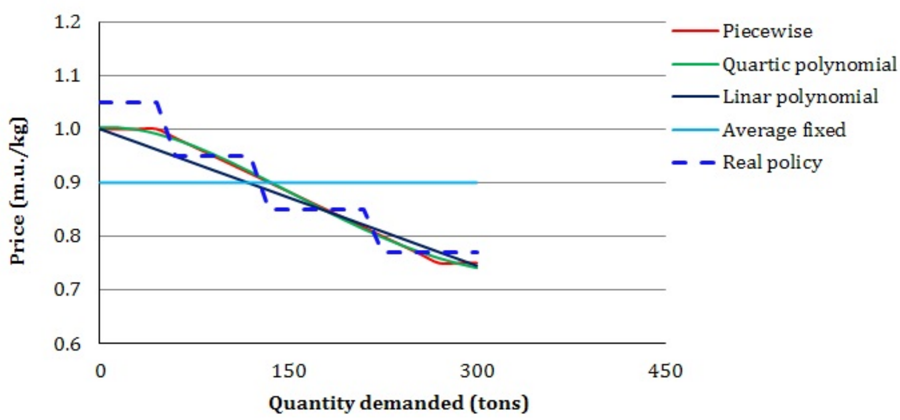
1.2
1.1
1.0
0.9
0.8
0.7
0.6
Price (m.u./kg)
0
150
300
450
Quantity demanded (tons)
Piecewise
Quartic polynomial
Linear polynomial
Average fixed
Real policy

(a) $rm1$

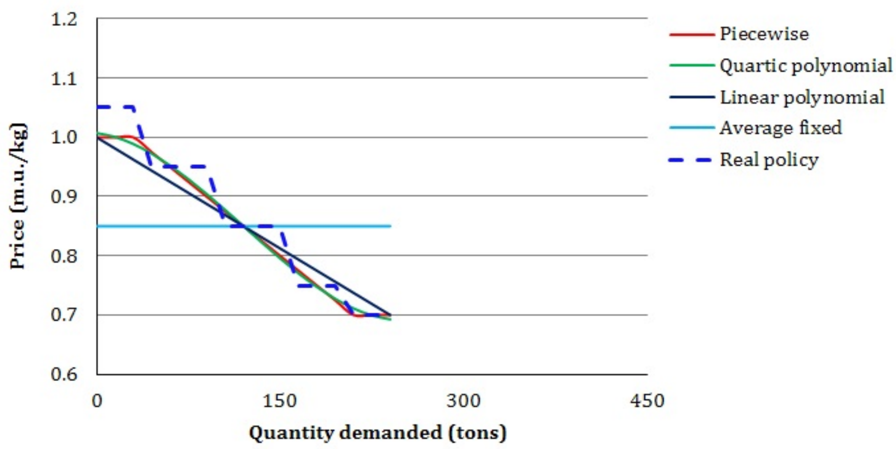


1.2
1.1
1.0
0.9
0.8
0.7
0.6
Price (m.u./kg)
0
150
300
450
Quantity demanded (tons)
Piecewise
Quartic polynomial
Linar polynomial
Average fixed
Real policy

(b) $rm2$

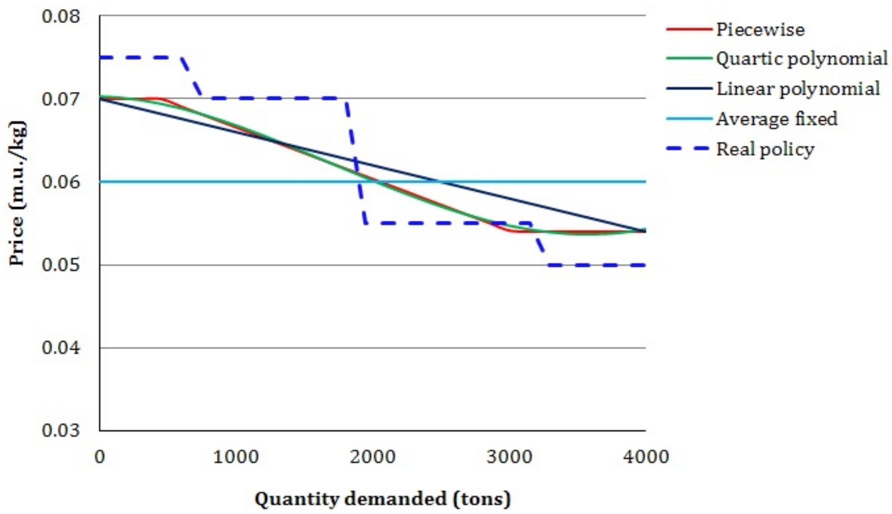


(c) $rm3$

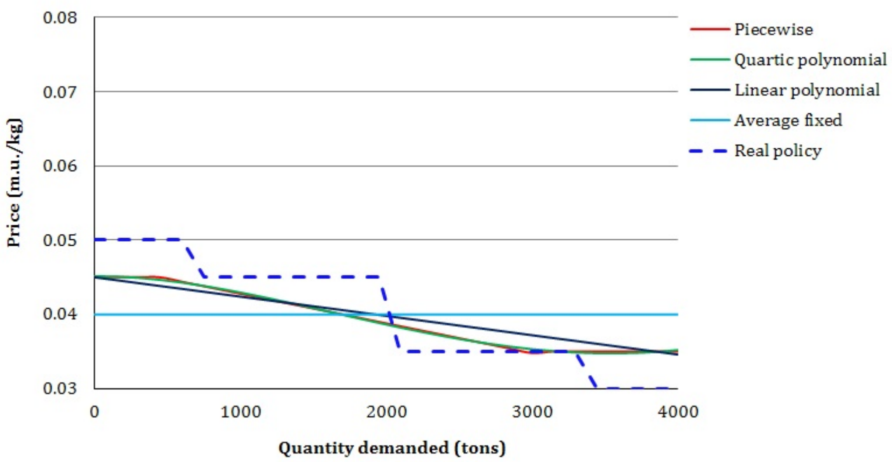


(d) $rm4$

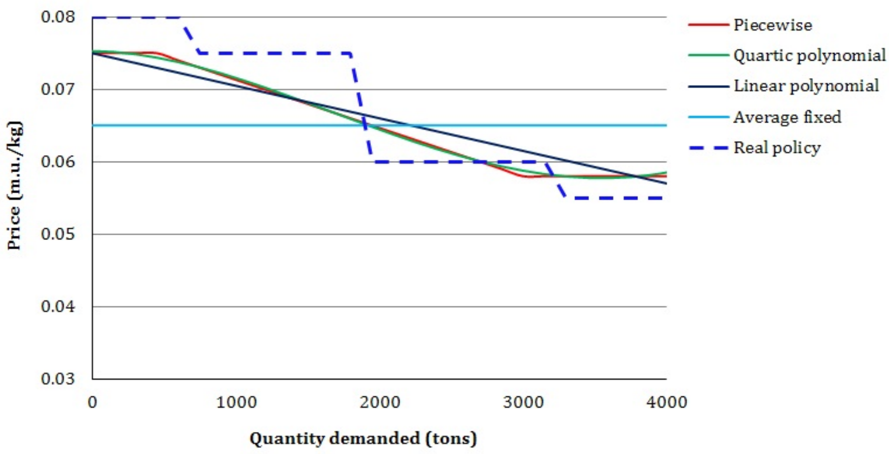
Figure 5.7: Polystyrene SC third parties pricing trends


Price (m.u./kg)
0.08
0.07
0.06
0.05
0.04
0.03
0
1000
2000
3000
4000
Quantity demanded (tons)
Piecewise
Quartic polynomial
Linear polynomial
Average fixed
Real policy

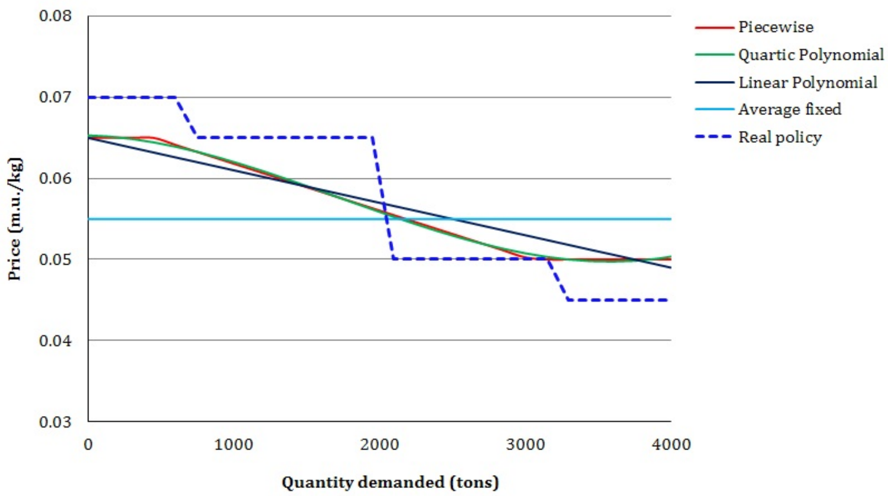
(a) $b1$


Price (m.u./kg)
0.08
0.07
0.06
0.05
0.04
0.03
0
1000
2000
3000
4000
Quantity demanded (tons)
Piecewise
Quartic polynomial
Linear polynomial
Average fixed
Real policy

(b) $b2$



(c) $b3$



(d) $b4$

Figure 5.8: Energy SC third parties pricing trends

Fixed pricing

Table 5.1 summarizes the resources average fixed prices resulting from the average fixed pricing approximation.

Table 5.1: Resources average fixed prices

Resource	Price (m.u./kg)
$rm1$	1.00
$rm2$	0.90
$rm3$	0.90
$rm4$	0.85
$b1$	0.060
$b2$	0.040
$b3$	0.065
$b4$	0.055

Polynomial pricing

Two polynomial trends are considered and compared for this study: quartic polynomial (with polynomial degree 4) and linear polynomial (with polynomial degree 1) (see Figures 5.7 and 5.8). The characteristics of the polynomial pricing approximation model (Eq. (5.3)) are illustrated in Table 5.2

Table 5.2: Polynomial pricing approximation parameters

	Quartic polynomial					Linear polynomial	
Raw material	$c1$	$c2$	$c3$	$c4$	$c5$	$c1$	$c2$
$rm1$	8.43E-25	7.61E-18	-5.03E-12	5.04E-09	1.155	-6.0E-07	1.15
$rm2$	-2.32E-23	2.95E-17	-1.01E-11	1.43E-07	1.003	-8.5E-07	1.00
$rm3$	-2.32E-23	2.95E-17	-1.01E-11	1.43E-07	1.003	-8.5E-07	1.00
$rm4$	0	3.68E-17	-1.33E-11	-2.50E-07	1.007	-1.25E-6	1.00
$b1$	-2.5E-29	8.82E-22	-4.05E-15	-2.89E-10	0.070	-4.0E-09	0.070
$b2$	-3.6E-29	7.33E-22	-3.01E-15	1.26E-10	0.045	-2.6 E-09	0.045
$b3$	-3.6E-29	1.03E-21	-4.54E-15	-1.54E-10	0.075	-4.5 E-09	0.075
$b4$	-1.3E-29	7.36E-22	-3.56E-15	-4.25E-10	0.065	-4.0E-09	0.065

Piecewise pricing

For this study, three pricing zones are considered (n=3) for each third party resource feeding the global SC. The price elasticity of demand (ED) for the first and the third pricing zones (n=1 & n=3) is equal to zero. All competitive third parties offer price discounts at zone 2 (n=2) based on the price elasticity of demand theory. The price elasticity of demand is considered (-20) for the third party resources feeding the polystyrene production SC echelon, and (-25) for the resources feeding the energy generation SC echelon.

Table 5.3 summarizes the parameters needed to implement the piecewise linear pricing model (see also Figures 5.5, 5.7, and 5.8).

Table 5.3: Piecewise approximation parameters

	Prices constraints (m.u./kg)		Quantity constraints (tons)		
	max. price	min. price	max. zone 1	max. zone 2	max. zone 3
$rm1$	1.15	0.86	60	360	450
$rm2$	1.00	0.75	45	270	300
$rm3$	1.00	0.75	45	270	300
$rm4$	1.00	0.70	30	210	240
$b1$	0.070	0.054	450	3,000	4,000
$b2$	0.045	0.035	450	3,000	4,000
$b3$	0.075	0.058	450	3,000	4,000
$b4$	0.065	0.050	450	3,000	4,000

5.5 Results and discussions

The proposed pricing approximation models, within the global SC framework, are implemented to the above case study considering third parties prices policies, resources balances, processes availability, and capacities over 10 time periods planning horizon; 1000 working hours each. The resulting LP, NLP, and MINLP models are modeled using GAMS and solved using different optimization packages on Windows 7 computer with Intel Core$^{\text{TM}}$ i7-2600 CPU 3.40GHz processor with 16.0 GB of RAM.

5.5.1 Solution procedure

The solution procedure is divided into two steps: i) optimization, and ii) simulation.

i) Optimization step:

The optimization step involves in solving each pricing model (4 global tactical models), separately, under the objective function of minimizing the total SC cost. The optimal tactical decisions are obtained from this step, and compared for each pricing approximation model (resources flow distribution Q from the third parties, resources unit price P, production levels, storage levels, and distribution flows and directions).

ii) Simulation step:

Then, the optimal resources purchase flows Q from the third parties resulting from the optimization step (step i) are allocated to their real prices each time period (according to Figures 5.7 and 5.8). Then, the pricing approximation models are simulated using the optimal resources Q and their real prices to obtain the associated real total costs. These real total costs are compared with the total costs resulted from the pricing approximation models in order to find out the most adequate pricing approximation method.

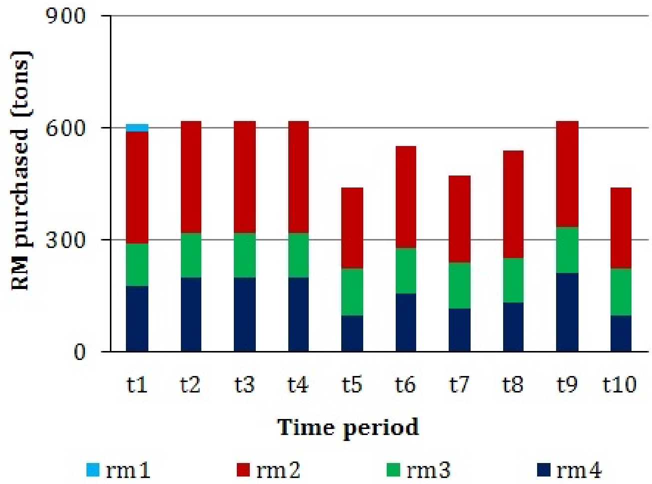
The results are analyzed and compared in order to evaluate the efficiency of these alternative pricing approximation approaches over the tactical decisions of the participating partners. The optimal tactical decisions resulted from the pricing approximation models are analyzed and compared to study their role in capturing the competition among the interacting third parties. The results show that the selection of the pricing approximation approach affects the tactical decision-making of all participants.

In the next paragraphs, the effects of the pricing modeling on the tactical decision-making of both the polystyrene production SC echelon and the energy generation SC echelon are studied in details, and compared.

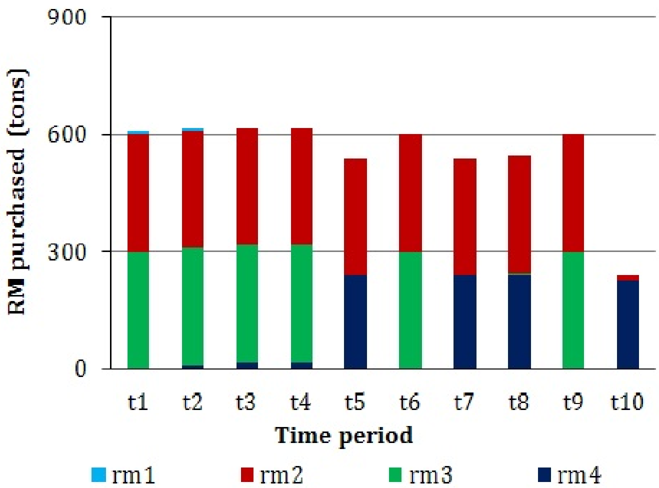
5.5.2 Results: polystyrene production SC

The results show that the pricing approximation models affect the tactical decision-making of the polystyrene production SC. The RM purchase levels from the third parties (suppliers) vary according to each pricing approximation model. For example, $rm1$ and $rm2$ suppliers compete to deliver for producing polystyrene product A, while $rm3$ and $rm4$ suppliers compete for polystyrene product B. It is noticed in Figure 5.9 that $rm2$ and $rm4$ dominate the RM purchase amounts using most of the pricing approximation approaches, except the piecewise pricing approach. The dominance of $rm2$ is due to it lower prices than $rm1$ (see Figure 5.7) and less distance to the dominant polystyrene production plants ($pl2$ and $pl3$) (see Table Appendix B.10 and Figure 5.11).

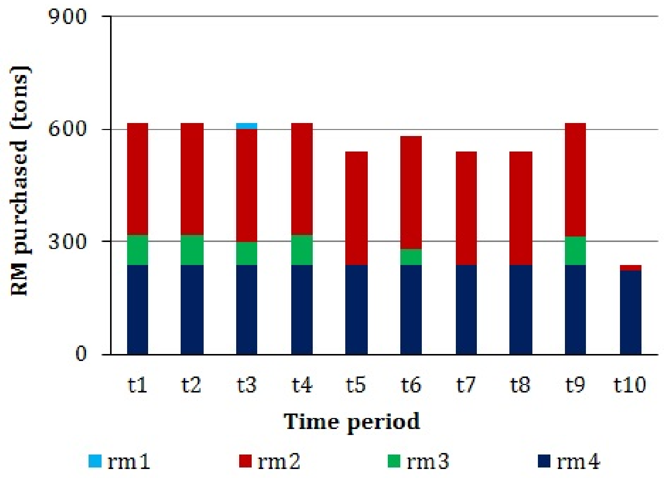
The trend of using the price approximation models, considering price discounting policies, is to purchase high quantities of RM from the third parties in order to get higher discounts. This can be clearly seen in Figure 5.9(d); using the linear polynomial pricing approach leads to purchase $rm4$ up to its supplying capacity (240 tons) all time periods to produce product B, and $rm3$ at time periods $t1$, $t3$ and $t5$ also up to its supplying capacity in order to get the least price offer. This leads to excess products to be stored for later distribution, and to stop producing polystyrene product B at time periods $t4$ and $t10$ (Figure 5.12(d)). However, the trend of using the average fixed pricing approximation is to purchase from all RM suppliers (except $rm1$ due to its high price) at all time periods (Figure 5.9(a)), as its decisions do not consider any discounts.



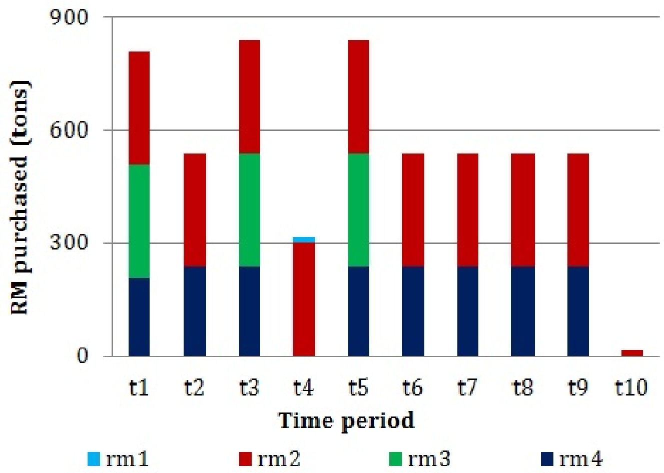
(a) Average fixed pricing



(b) Piecewise pricing



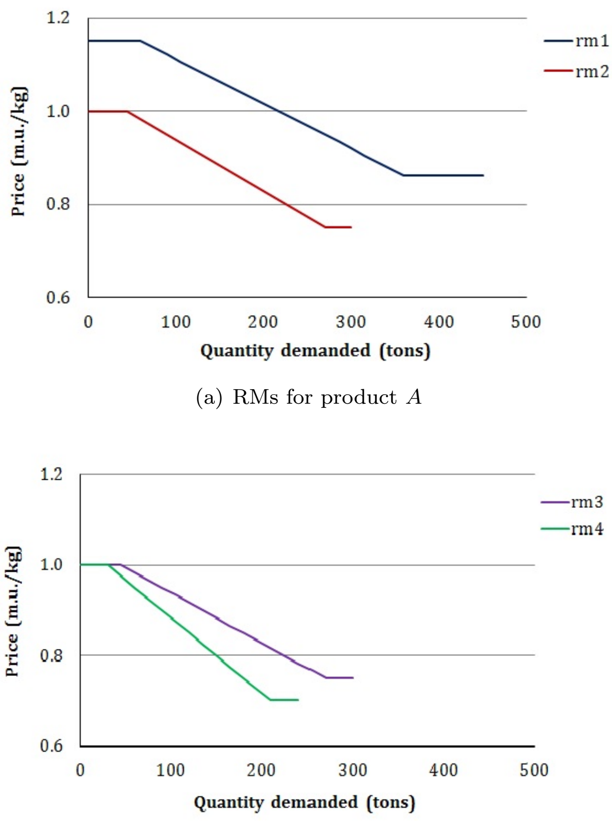
(c) Quartic polynomial pricing



(d) Linear polynomial pricing

Figure 5.9: Polystyrene SC RM purchased

Analyzing the results obtained from using the piecewise pricing approximation (Figure 5.9(b)), it is noticed that, rather than the rest of the pricing approaches, the $rm3$ supplier dominates the purchase orders most of the time periods for polystyrene product B production. Regardless of its higher price comparing with $rm4$, the difference between their prices is low (Figure 5.10(b)), so the trend is to purchase from the highest supplying capacity ($rm3$). At the contrary, although $rm1$ has higher supplying capacity than $rm2$, the decision is to purchase from the supplier of the last $rm2$ up to its capacity (300 tons) due to the large difference in their prices (Figure 5.10(a)). This leads to excess production of product A, to be stored and distributed later at higher demands periods (see Figure 5.11(b)), and this explains why the purchase level of $rm2$ is very low (16.40 tons) at time period $t10$. So, a trade-off can be seen between the supplying capacity and the RM unit price.

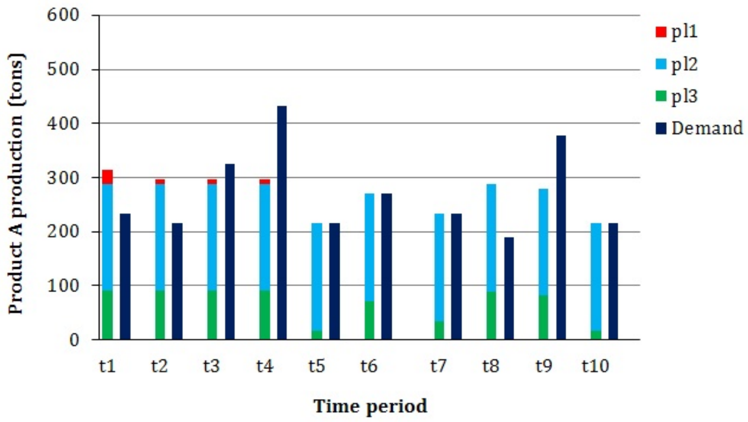


(a) RMs for product A

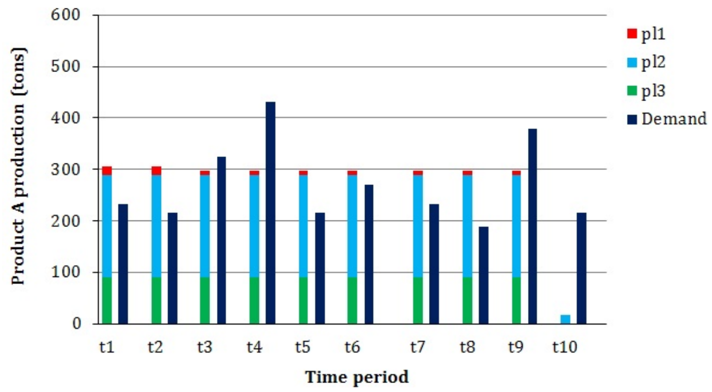
(b) RMs for product B

Figure 5.10: Piecewise pricing approximation analysis

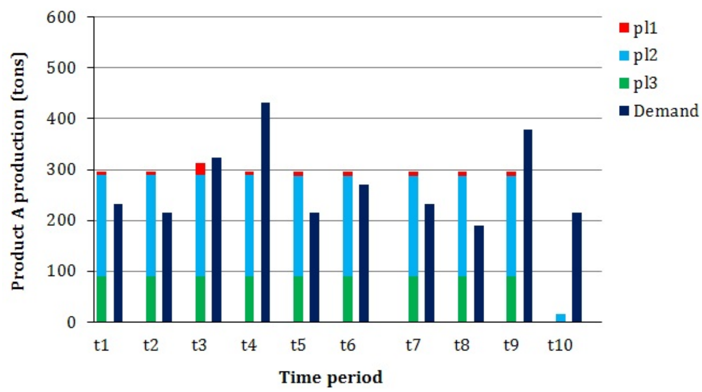
Consequently, the polystyrene production levels are affected by the selection of the pricing approximation approach (Figures 5.11 and 5.12). For example, the polystyrene production levels of product A (Figure 5.11) are affected by the RM $rm2$ purchase orders (Figure 5.9) resulted from the different pricing approximation models, since $rm2$ dominates the RM orders to produce product A. The selection of the RM supplier also affects the operation of the polystyrene production plants (produce or not). For example, the polystyrene production plant $pl2$ dominates producing polystyrene product A using all the pricing approximation approaches, as it is close to the $rm2$ supplier location (see Table Appendix B.10). Furthermore, the pricing approximation affects the efficiency of the coordination among the echelons SCs within the global SC network. For example, at $t10$, the production levels of product A (Figures 5.11(b)), 5.11(c), and 5.11(d)) are very low although the final customer demand is still high. This is due to the high purchase levels of $rm2$ at te first time periods leading to excess production, so this demand can be satisfied by the stored products in the previous time periods (Figure 5.13).



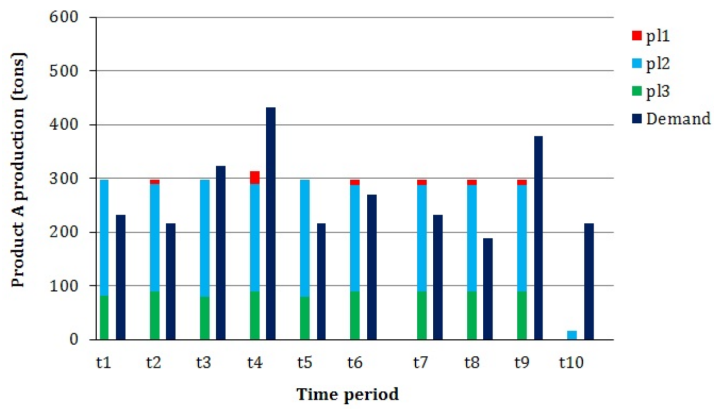
(a) Average fixed pricing



(b) Piecewise pricing



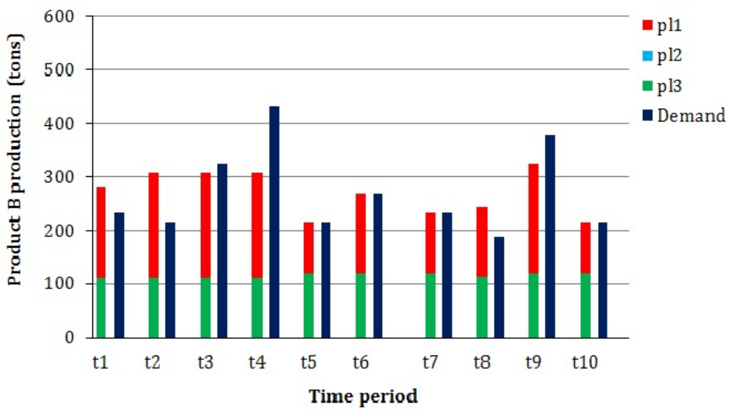
(c) Quartic polynomial pricing



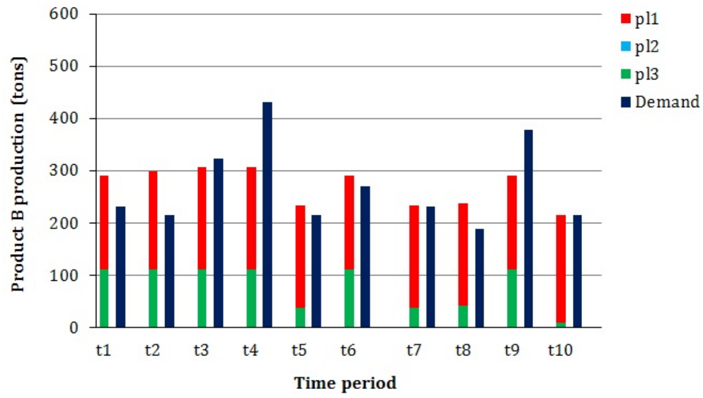
(d) Linear polynomial pricing

Figure 5.11: Polystyrene product A production

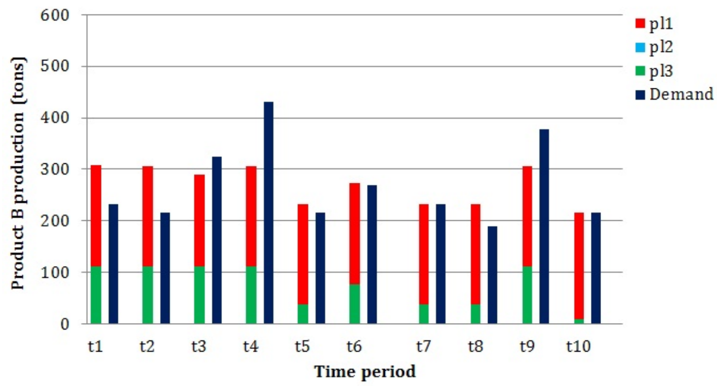
Figure 5.12 illustrates the polystyrene production decisions of product B. It is noticed that the polystyrene production plants $pl1$ and $pl3$ dominate the production levels of product B in the majority of the pricing models. This can be explained due to the dominance of the RM supplier of $rm4$ to produce product B, as the polystyrene production plant $pl1$ has the closest distance with the $rm4$ supplier $sup4$ location (see Table B.10). This can be seen clearly in Figure 5.12(b) using the piecewise pricing approach, the production plant $pl1$ dominates the production levels of product B at time periods $t5$, $t7$, $t8$ and $t10$, when the $rm4$ dominates the RM purchase orders. However, the decision using the linear polynomial pricing approach is to operate the polystyrene production plant $pl2$ besides the other production plants to produce product B at time periods $t1$, $t3$ and $t5$ (Figure 5.12(d)). This can be explained due to the high purchase orders of $rm3$ at those time periods (Figure 5.9(d)), considering that the polystyrene production plant $pl2$ is the closest to the $rm3$ supplier location. This stresses the distribution role in the global coordination.



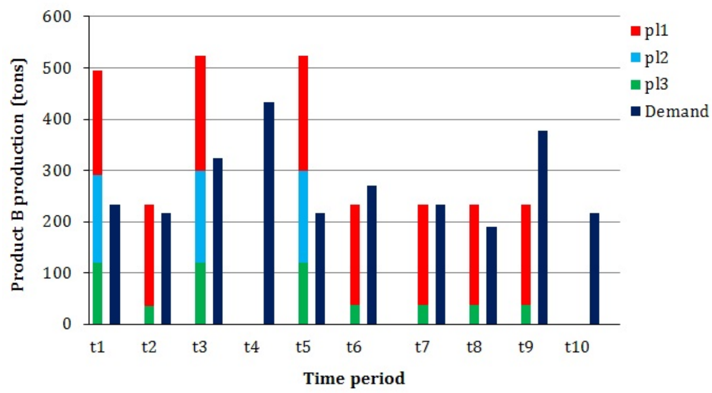
(a) Average fixed pricing



(b) Piecewise pricing



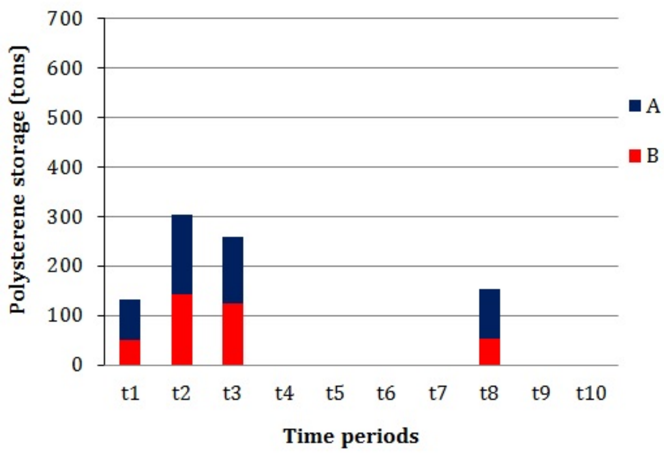
(c) Quartic polynomial pricing



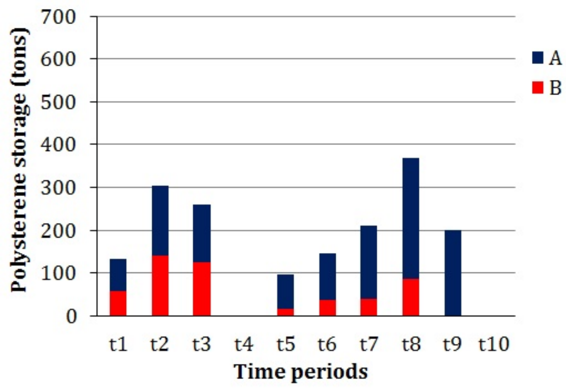
(d) Linear polynomial pricing

Figure 5.12: Polystyrene product B production

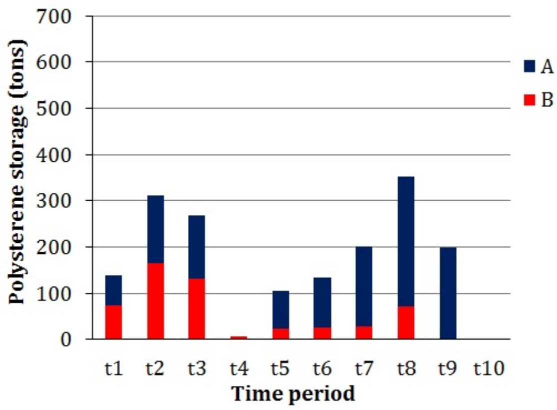
As it is mentioned before, the storage action has a potential role in this study (Figure 5.13). Using prices discounts through the different proposed pricing approximation approaches drives the decision-maker to purchase higher quantities of raw materials in order to obtain lower prices. This leads to produce extra products (A and B) to be stored for later distribution in further time periods. The role of the storage actions in the discounting pricing models can be see in Figures 5.13(b), 5.13(c), and 5.13(d); the discounting pricing models result in higher storage levels than the average fixed pricing model (Figure 5.13(a)). The linear polynomial approximation model results in the highest total storage amounts (3802 tons) (Figure 5.13(d)), in comparison with the average fixed pricing (842 tons), piecewise pricing (1718 tons), and the quartic Polynesian pricing (1721 tons). The average fixed pricing approximation model yields the lowest storage amounts, as strategy does not consider any discounts. It is noticed that the piecewise and quartic polynomial pricing approximation models result in high storage levels of polystyrene product A at time periods $t7$, $t8$ and $t9$ (Figures 5.13(b), 5.13(c)). This is due to the high production levels of product A in those time periods, so that the excess amounts are stored and distributed at time $t10$, where the production action is very low (Figures 5.11(b) and 5.11(c)).



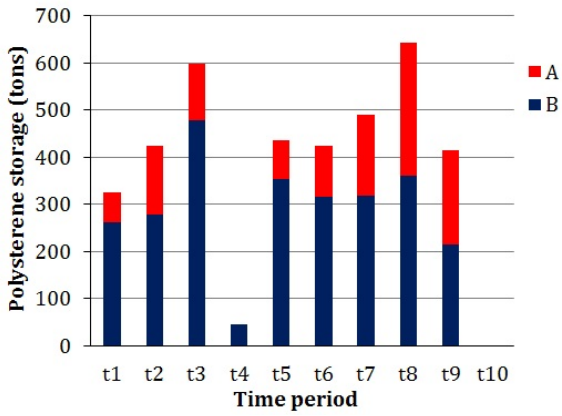
(a) Average fixed pricing



(b) Piecewise pricing



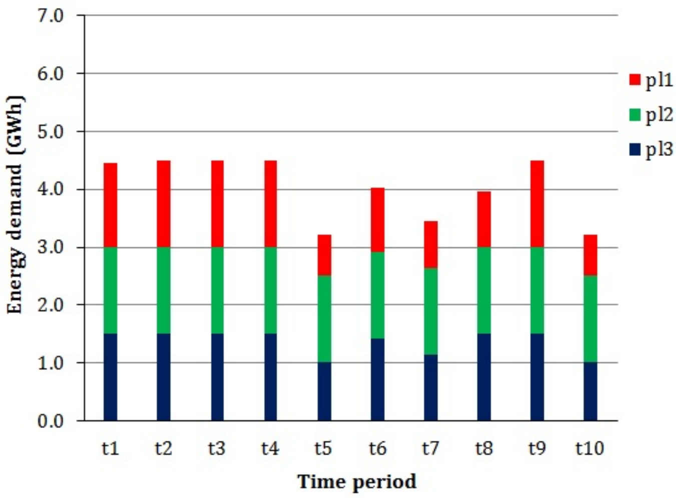
(c) Quartic polynomial pricing



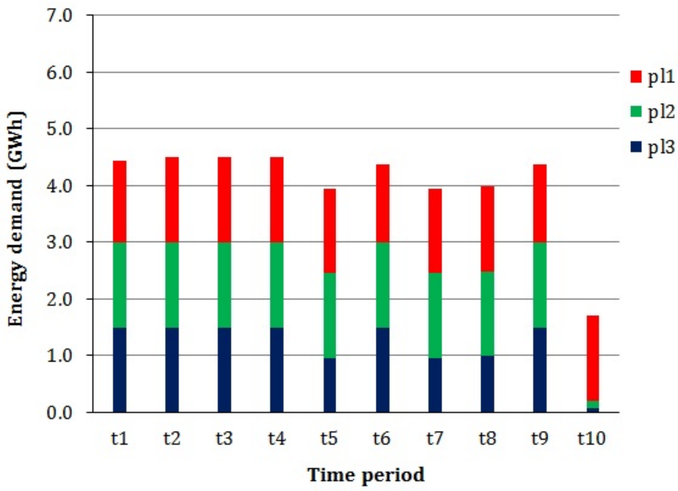
(d) Linear polynomial pricing

Figure 5.13: Polystyrene storage levels

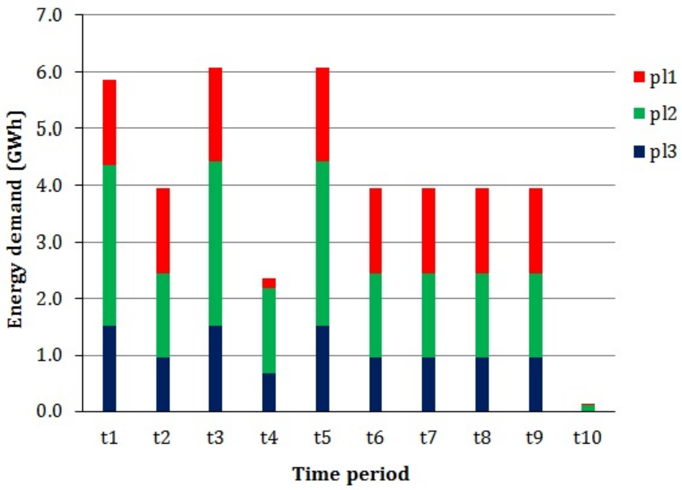
The internal energy demand by the polystyrene SC production plants (the coordination item) is also affected by the pricing approximation modeling (Figure 5.14). It is noticed that the internal energy demands follow the polystyrene production activities, which are affected by the pricing modeling. For example, the internal energy demand using the linear polynomial pricing modeling (Figure 5.14(d)) is high at time periods $t1$, $t3$ and $t5$, as the polystyrene production levels are very high in those time periods to produce product B.



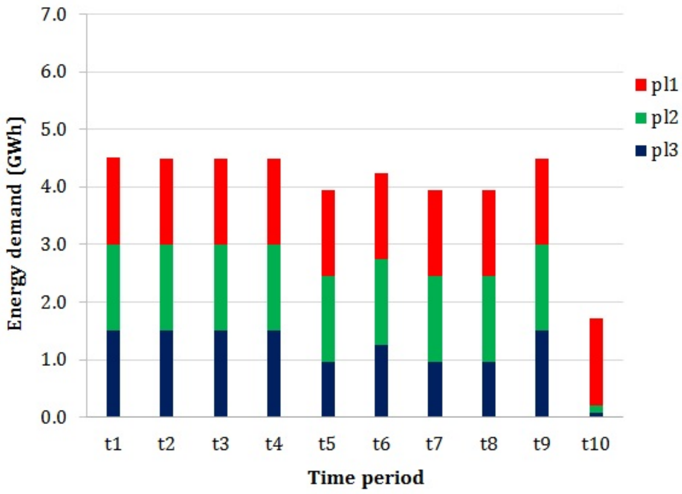
(a) Average fixed pricing



(b) Piecewise pricing



(c) Quartic polynomial pricing



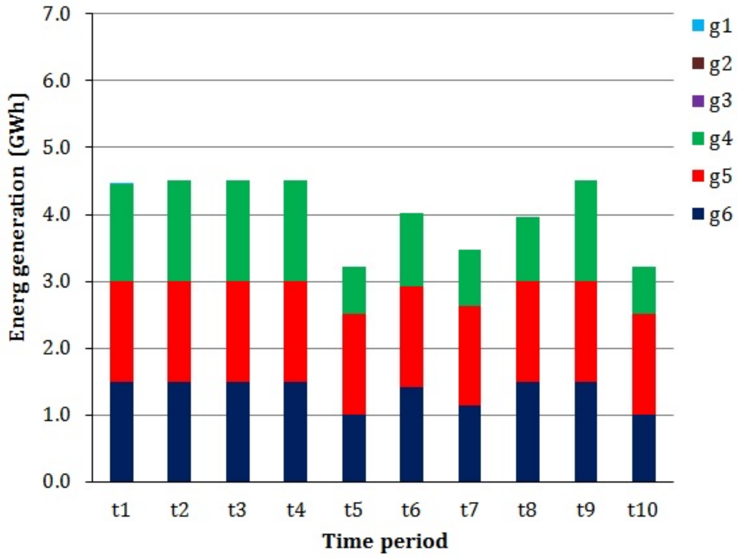
(d) Linear polynomial pricing

Figure 5.14: Internal energy demand

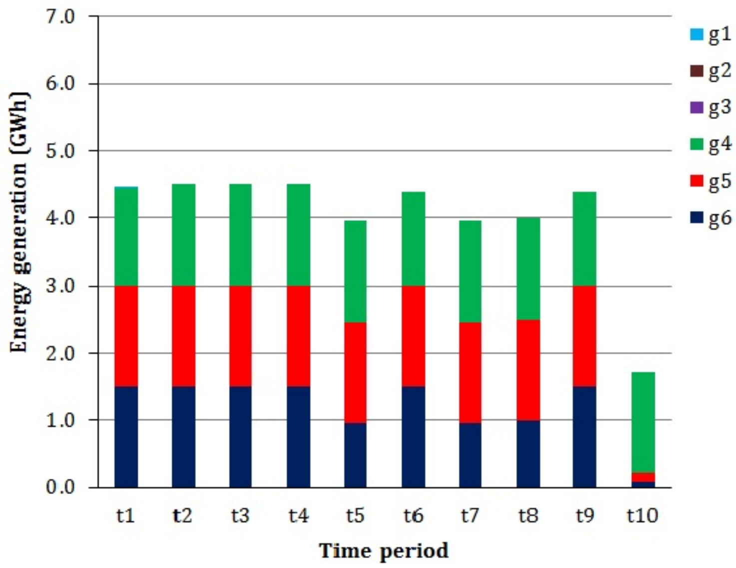
5.5.3 Results: energy generation SC

Consequently, and within the coordination framework, the pricing modeling leads to changes in the tactical decision-making of the energy generation SC echelon (Figure 5.15). According to the coordination requirements, the energy generation SC has to fulfill the energy demanded by the polystyrene SC (Figure 5.14) besides the other external energy markets. It is noticed in Figure 5.15 that the energy generation plants $g4$, $g5$ and $g6$ (combustion technology) dominate the energy generation levels using most of the pricing approximation approaches, except the linear polynomial approach. Most of the pricing approximation models result in closing the energy generation plants $g1$, $g2$ and $g3$ (gasification technology).

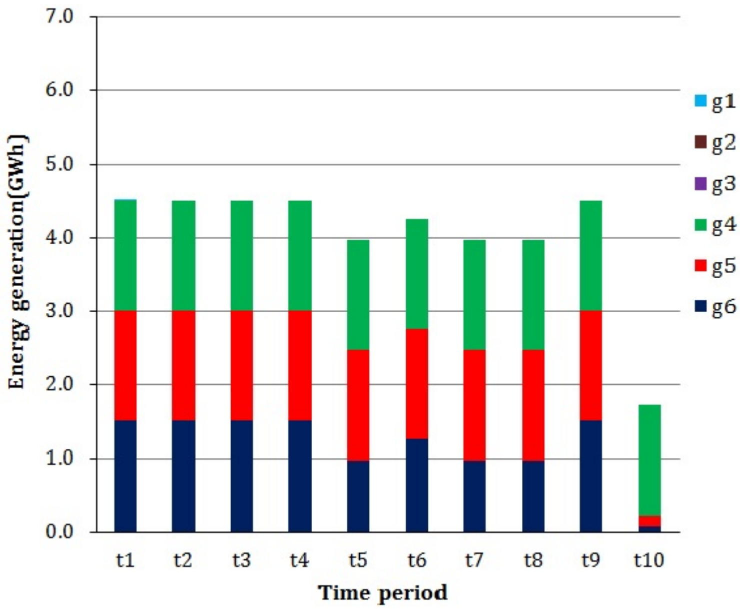
However, the linear polynomial model leads to operate the energy generation plants $g1$ and $g2$ at time periods $t1$, $t3$ and $t5$ when the energy generation plants $p4$ and $p5$ exceed their capacities in order to follow the high energy demand by the polystyrene production plants at those time periods resulted from purchasing high RM amounts (see Figure 5.9(d)). Furthermore, the linear polynomial pricing approximation model results in very low energy generation level at time period $t10$ (128 MWh; 0.32 % of the total energy generation) (Figure 5.15(d)) due to the low polystyrene production level resulting from the small purchase amount of RM at this time period (see Figures 5.9(d) and 5.14(d)). It is also noticed that the piecewise and the quartic polynomial approximation models result in similar energy generation levels most of the time periods (Figures 5.15(b) and 5.15(c)). However, at time period $t6$, the piecewise pricing model leads to operate the energy generation plant $g6$ up to its generation capacity (Figure 5.15(b)) in order to cope with the high energy demand resulting from operating the polystyrene production plant $pl3$ (Figure 5.12(b)) resulting from the high raw material $rm3$ order amounts at this time period (Figure 5.9(b)).



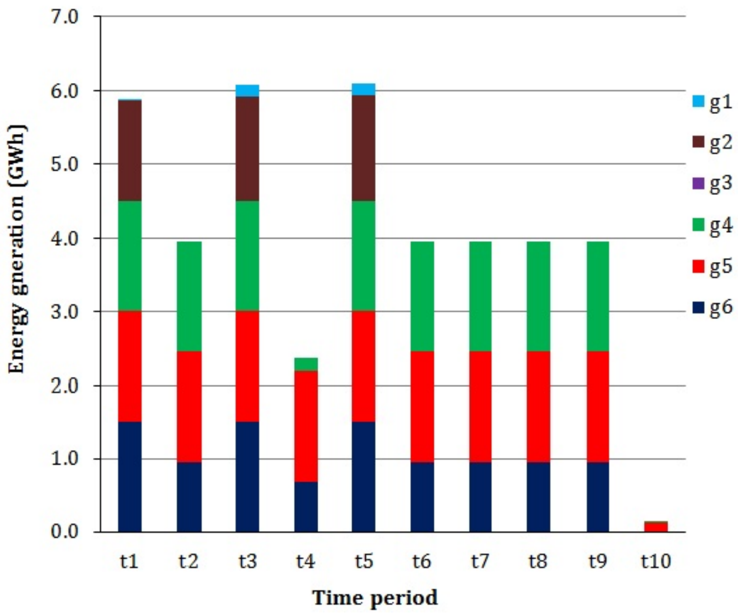
(a) Average fixed pricing



(b) Piecewise pricing



(c) Quartic polynomial pricing



(d) Linear polynomial pricing

Figure 5.15: Energy generation levels

Consequently, the raw materials orders for the energy generation vary according to the pricing approximation method (Figure 5.16). It is noticed that the raw material $b2$ supplier dominates the supplying orders using all the pricing approximation approaches. This can be explained by the operation of the energy generation plants $g4$, $g5$ and $g6$, in which the raw material $b2$ has the highest efficiency (2.6 kWh/kg) (see Table B.1), although the raw material $b1$ has the lowest price. Here it can be seen the trade-off between the efficiency and the price in the pricing modeling. However, the raw material $b2$ purchase quantities vary according to the pricing approximation modeling. For example, the linear polynomial approximation model results in purchasing the highest amounts of RM $b2$ (16,042 tons), especially at time periods $t1$, $t3$ and $t5$ to follow the energy demand resulting from purchasing high amounts of RM purchase for the polystyrene SC (see Figure 5.9(d)). It is also noticed that the piecewise and quartic polynomial approximation models lead to very low purchase quantities of raw material $b2$ at time period $t10$; 660 tons for the piecewise and the quartic polynomial pricing models, and 49 tons for the linear polynomial pricing model.

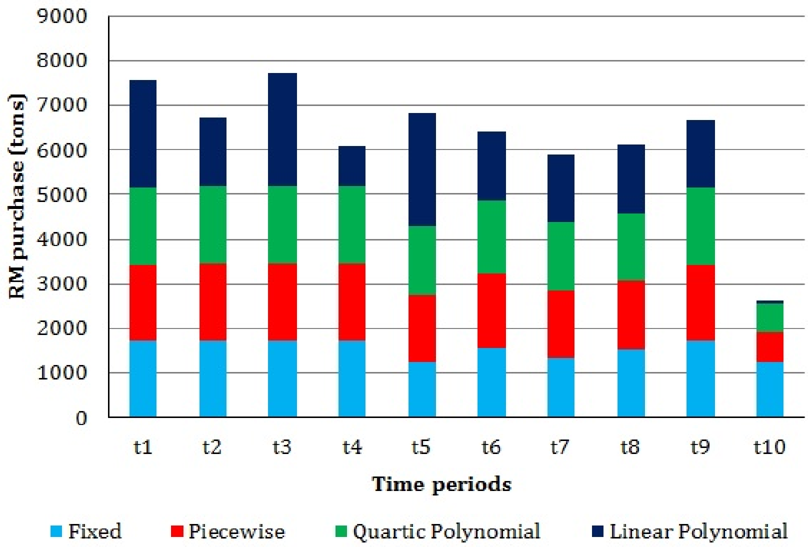


Figure 5.16: Energy SC raw material purchase levels

5.5.4 Economic analysis

After obtaining the decisions resulting from each pricing approximation model, the simulation step starts to obtain the real total costs corresponding to these optimal decisions. The tactical RM purchase levels obtained from the different pricing models (Figures 5.9 and 5.16) are allocated to their corresponding real prices following the 3rd parties prices policies as in Figures 5.7 and 5.8). It is worth to remind that the real prices policies of the 3rd parties are complex to model, so different pricing approximation models are proposed to estimate these policies and to obtain the optimal RM purchase orders from the 3rd parties. Then, in order to compare these pricing approximations, the pricing models are simulated considering the optimal RM purchase amounts and their real prices to obtain the real total costs considering the original price policy.

The total SC cost resulted from the different pricing approximation models are illustrated and compared with the real total costs in Figures 5.17 and Table 5.4. It is noticed that the piecewise pricing approximation results in the lowest real total cost (16.42 x10^6 m.u.). The linear polynomial and the average fixed pricing approximation models lead to the worst decisions resulting in the highest real total costs; 16.58 x10^6 m.u. and 16.57 x10^6 m.u., respectively (Table 5.4). Unexpectedly, the traditional average approximation method leads to the highest RM purchase cost (5.08 x10^6 m.u.); 4.3 %, 6.4 % and 3.5% higher than the quartic polynomial, linear polynomial, and piecewise pricing approximation models, respectively. The trend of the fixed pricing approximation model does not allow the 3rd parties to flexibly control their financial nodes, giving them less margins to compete.

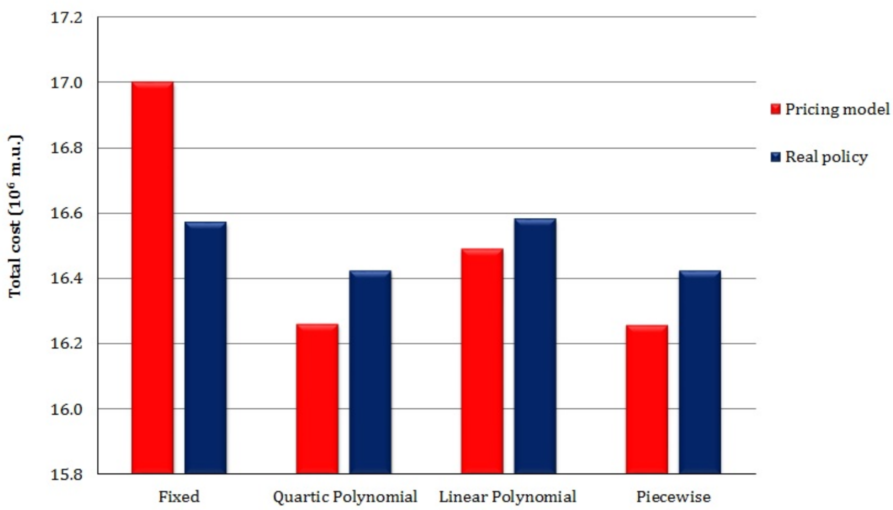


Figure 5.17: SC total cost (pricing models vs. real policies)

Table 5.4 summarizes the model statistics of the proposed pricing approximation models. It is noticed that the most adequate pricing approximation method (piecewise approximation) requires higher computational efforts (CPU = 5.8 sec.) than the others, while the worst pricing approximation requires less computational efforts (CPU = 0.05 sec.).

Table 5.4: Models statistics

						Total cost (10^6 m.u.)	
	Model	Single equations	Single variables	Discrete variable	CPU (sec)	Pricing	Real
Fixed	LP	2,752	4,991	-	0.05	17.00	16.57
Piecewise	MINLP	3,336	5,495	240	5.80	16.26	16.42
Quartic Polynomial	NLP	2,952	5,191	-	0.13	16.26	16.42
Linear Polynomial	NLP	2,952	5,191	-	0.11	16.49	16.58

An important point arises here is to find another fixed pricing approximation, rather than the average one, that leads to better decisions of lower real total costs. To examine this point, different fixed pricing approximation models have been developed to estimate the 3^{rd} parties prices polices. Each real price policy pattern is divided into five ranges: maximum price (F1), two intermediates prices (F2 & F4), minimum price (F5), besides the average fixed model analyzed before (here named as F3) (Table 5.5). The optimal RM purchase orders resulted from each fixed pricing model along the planning time horizon are obtained. Then these RM amounts are allocated to their corresponding real prices as in Figures 5.7 and 5.8. The fixed pricing models are simulated using the optimal RM amounts and their corresponding real prices to obtain the real total costs. Figure 5.18 and Table 5.5 illustrate the total costs resulting from the optimization and the simulation models of the different fixed pricing approximations (pricing vs. real total costs). It is noticed that the optimal RM purchase orders resulted from the fixed pricing approximation model (F4) lead to the best real total cost (16.42 x10^6 m.u.), which is similar to the total real costs resulted from the piecewise pricing model (see Table 5.4). Unlike the traditional way to approximate real price policies, the average price approximation (F3) leads to the worst decisions resulting in the highest total real cost (16.57x10^6 m.u.).

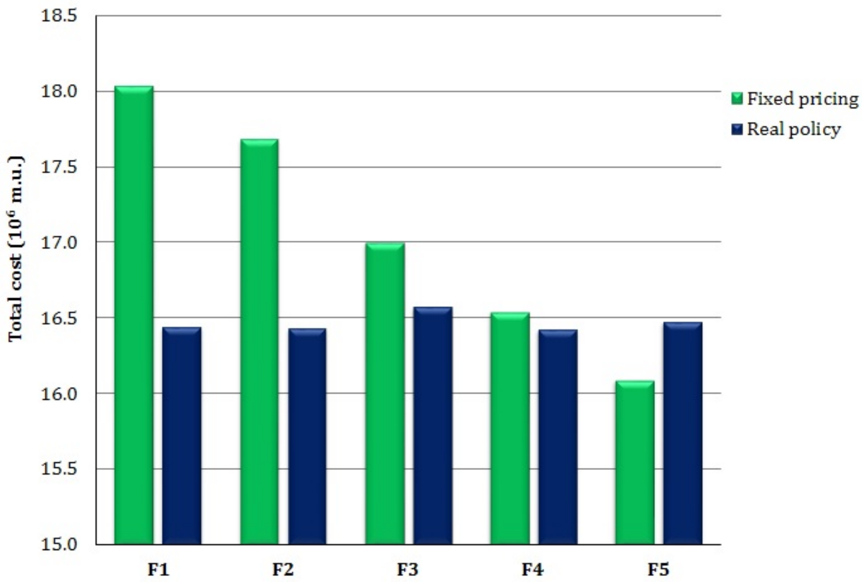


Figure 5.18: SC total cost (fixed pricing models vs. real policies)

Table 5.5: Fixed pricing and real total costs

	Total cost (10^6 m.u.)	
	Fixed pricing	Real policy
F1 (maximum)	18.04	16.44
F2 (intermediate)	17.68	16.43
F3 (average)	17.00	16.57
F4 (intermediate)	16.54	16.42
F5 (minimum)	16.09	16.47

5.6 Final considerations

A generic coordinated global model is proposed integrating the decisions of the third parties as part of the decision-making procedure. The third parties price policies are incorporated into the coordinated model formulations as degree of freedom decisions, giving them flexibility to participate in the global decision-making of multi-site multi-echelon multi-product production-distribution SC.

Different pricing approximation models are proposed and compared to estimate the third parties prices complex policies based on fixed, piecewise and polynomial approximations. This results in LP, NLP, and MINLP models to be solved using different solution packages. The advantages of using the different pricing approximation models on the SC global coordination and the tactical decision-making are illustrated using a case study extended from Chapter 4 that coordinates the polystyrene production SC with an energy generation SCs considering their competitive third parties. The results show that integrating the third parties decisions in the global tactical model allows them to participate as partners in the decision-making process, and thus giving them enough margins to compete. Dealing with the third parties pricing as a collaborative tool rather than fixed economic transactions gives the third parties enough freedom to participate and control their financial channels, so to be able to compete in the global market environment.

Furthermore, the results show that the proposed pricing approximation models significantly affect the global SCs coordination, resulting in different tactical and economic decisions for all participants. The trend of the global SC using the discounting pricing models based on piecewise and polynomial approximations is to order higher amounts of resources from the third parties in order to get lower prices. This results in extra production, taking the advantage of the storage to store the excess products for later distribution resulting in different economic performance. Comparing with the real total costs resulting from the different pricing approximation models, the piecewise pricing approach leads to the best pricing approximations with significant savings (4.6 %) in terms of the total cost, in comparison with the average fixed pricing approximation. So, the traditional average pricing approximation is not recommended.

The proposed global coordinated tactical models are generic and flexible enough to be extended to cope with more SCs interactions and echelons, in which each echelon SC, including the third parties can play different roles; clients on one hand and providers on the other hand. Furthermore, the pricing models can be considered as base line for further inter-organizational negotiations.

By this chapter, a global coordinated framework is developed taking into consideration the decisions of all participants, including their competitive third parties, based on negotiations built on cooperative actions. In Part II (Chapters 4 and 5), the main production SC enterprise is obliged to cooperate with the provider SC, as it cannot function at the standalone case. However, what if all participants have standalone positive revenues, in which the coordination based on cooperative negotiations becomes risky, as all participants will seek to optimize their individual revenues, regardless of the other participants decisions and their uncertain reaction resulted from the uncertainty of their third parties price policies, all in uncertain competitive environment. This makes inter-organizational coordination/collaboration a must, based on non-cooperative approaches, as will see in the next part.

5.7 Nomenclature

Indices

e	echelon (production plant, distribution center, market,...)
r	resource (raw material, product, energy, steam, cash,...)
t	time period

Sets

D	Third parties echelons
E	echelons (production plant, distribution center, market...)
M	final customer
N	number of piecewise pricing zones
R	resource (raw material, product, energy, steam, cash,...)
T	time period

Parameters

$c_{a,r}$	parameter depends on the polynomial grade a of resource r
$ED_{r,e',e,t,n}$	price elasticity of demand of resource r purchased from echelon e' (third party) to echelon e at price zone n, time t
$Pf^{max}_{r,e',t}$	maximum price at echelon e' (third party), time t
$Pf^{min}_{r,e',t}$	minimum price at echelon e' (third party), time t
$P^{max}_{r,e',t,n}$	maximum price of resource r at echelon e' (third party), price zone n, time t
$P^{min}_{r,e',t,n}$	minimum price of resource r at echelon e' (third party), price zone n, time t
$Q^{max}_{r,e',e,t,n}$	maximum amount of resource r in price zone n at echelon e' (third party), time t

Continuous variables

$CRM_{e,t}$	cost of the externally supplied resources at echelon e, time t
$P_{r,e',t}$	Price of resource r at echelon e' (third parties), time t
$Pn_{r,e',t}$	Price of resource r at echelon e' (3^{rd} party), price zone n, time t
$Q_{r,e',e,t}$	resource r purchased from echelon e' (3^{rd} party), time t
$Qn_{r,e',e,t,n}$	resource r purchased from echelon e' (3^{rd} party) to echelon e at price zone n, time t

Discrete variables

$x_{r,e',t,n}$	Binary variable for pricing zone n of resource r at echelon e' (3^{rd} party), time t

Part III

Inter-Organizational Coordination/Collaboration under Uncertain Competitiveness

Chapter 6

Scenario-Based Dynamic Negotiation (SBDN) under Uncertainty

6.1 Introduction

The previous part of this thesis (Part II) covers the global SCs coordination (SCsCo) through synchronizing the SCs activities between the cooperating enterprises. The third parties have been integrated into the global decision-making process through their price policies as collaboration tools rather than fixed economic transactions. All participants cooperate to enhance the total system performance.

However, due to the globalization and market dynamics, chemical industry SCs enterprises seek "value reservation" in order to stay competitive (Grossmann, 2004). Current PSE literature focus on the optimization of chemical industry SCs under the decision-making of one player (centralized decision-maker). However, this may not be feasible, especially when dealing with large-scale SCs with independent enterprises participating as complete production SCs, in which they can operate at the standalone case. Each enterprise will really seek to optimize its individual revenues, regardless of the risk associated with the uncertain reaction of the other interacting partners resulted from the uncertain behavior of their third parties. Thus, the complexity arises when synchronizing the tactical decisions of the global decentralized SC under the different (contrasting) goals of the different participants.

The resolution of this complexity through cooperative/non-cooperative negotiations has been slightly studied in the PSE literature, as described in Chapter 2. Most of the reviewed literature, either for cooperative or non-cooperative organizations, deal with simple SC structures, in which the negotiating partners are forced to collaborate (no standalone revenues). The reviewed literature tends to reduce the role of the follower partner in the decision-making process by simplifying its SC model. By doing so, much information is lost leading to sub-optimal decision-making. Furthermore, none of the reviewed literature, although it is important, considers the uncertain behavior of the supporting enterprises (third parties) in the decision-making process, in which may lead to future disruptions and possible lost of business partners from the global SC network. So effective negotiations able to capture the contrasting goals of the interacting enterprises through win-win coordination/collaboration contracts is a must, especially under uncertain external conditions.

Consequently, this chapter participates in the PSE literature by developing a novel decision-support tool able to optimize the tactical decisions of large-scale multi-enterprise SCs taking into consideration the individual goals of all participants (decentralized), including the third parties. Cooperative and non-cooperative systems are analyzed and compared through negotiations. The boundary of the SC of interest from Part II is expanded to consider the presence of external clients and providers with certain behaviors.

A novel Scenario-Based Dynamic Negotiation (SBDN) approach that constitutes in the PSE by proposing to set the best conditions for coordination/collaboration contracts between the enterprises of contrasting objectives through identifying and managing new win-win scenarios. The negotiating partners (provider and client) participate as complete production SCs, functioning at the standalone case, in a multi-enterprise large-scale SC under uncertainty. The interaction between the negotiating partners with their respective contrasting objectives is captured through non-cooperative non-zero-sum SBDN with non-symmetric roles. The client stakeholder (as the leader partner) builds a set of coordination/collaboration agreements anticipating the uncertain reaction of the provider (follower partner), which is subjected to uncertainty resulted from the uncertain nature of the third parties. This uncertainty is summarized in a single behavioral expression to be considered in the leader objective function, as a quantified probability of acceptance.

A novel decision-support method is proposed to evaluate the overall negotiation outcome, based on the probability distributions of the expected profits and risk behaviors, in comparison with the standalone cases. Finally, the proposed SBDN approach results in different MINLP models, which are generic and flexible enough to be applied to real-sized industries with centralized and decentralized decision-making systems.

6.2 Problem statement

The problem statement involves in a large-scale multi-enterprise multi-echelon multi-product SC network with decentralized decision-making system (Figure

6.1). The client production SC produces different products to final customers using diferent resources from external suppliers and providers (main provider and third parties). The client SC can operate at the standalone case using the different resources from the external suppliers and providers. On the other hand, the main provider SC produces different products to final customers; external clients; and the main client. The inner component between the main provider and the main client is considered the negotiation item (Figure 6.1). To optimize the global decentralized decision-making under the different enterprises objectives, a complexity arises to identify the inner component (physical/economic) flows along the considered planning time horizon. The value of this inner product is an income to the main provider and a cost to the main client.

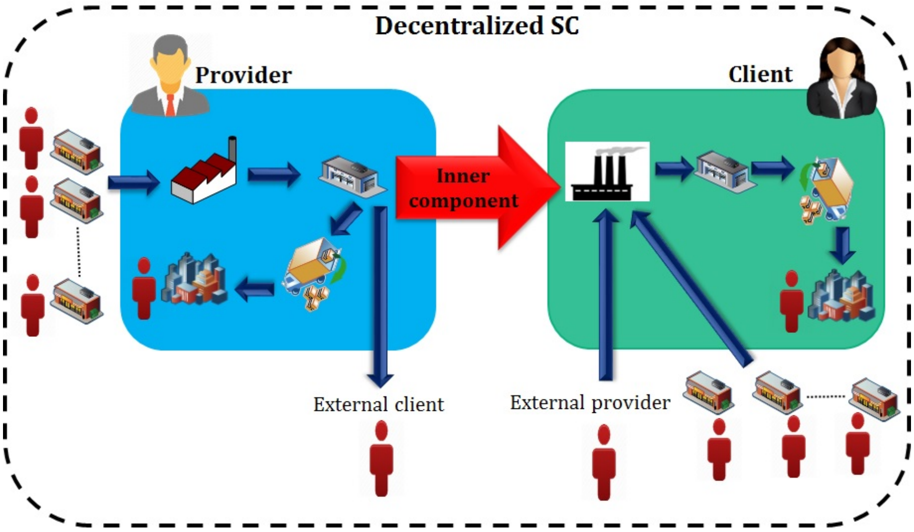


Figure 6.1: Decentralized SC network and stakeholders

6.3 Methodology

The coordination/collaboration is analyzed and compared based on cooperative and non-cooperative organizations, and compared with the standalone cases.

6.3.1 Scenario-Based Dynamic Negotiation (SBDN)

A non-cooperative non-zero-sum Scenario-Based Dynamic Negotiation (SBDN) approach with non-symmetric roles is proposed to capture the contrasting objectives of the negotiating partners under uncertainty. The main purpose of the proposed SBDN is to set the best conditions for the collaboration/coordination contract between the negotiating partners (main client and main provider), participating as complete production SCs in the SC of interest. Since any coordination contract is documented between pairs of stakeholders, the main client and the main provider are considered to sign the contract, while the other participants (e.g. suppliers, customers, external providers, external clients, etc.) are considered as third parties. These third parties participate in the decentralized decision-making procedure with their prices policies as proposed in Part II). The main items of the coordination/collaboration contract are the quantity flows of the inner component from the provider SC to each production plant of the client SC, and the unit transfer price at each time slot over the discrete planning time horizon (see Figure 6.2).

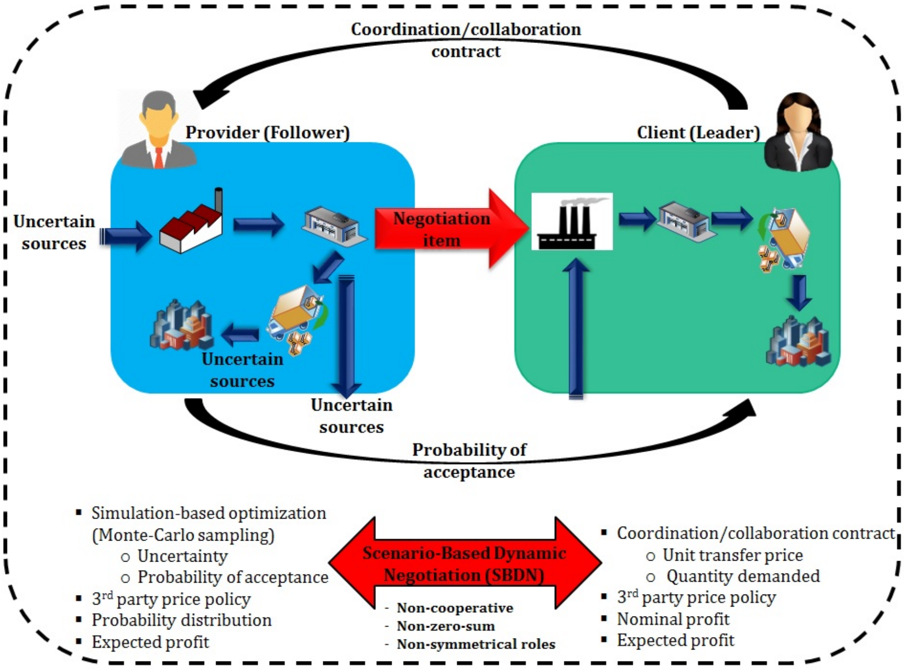


Figure 6.2: SBDN negotiation partners

Based on non-symmetric roles, the client decision-maker (as leader partner) builds a set of coordination/collaboration contracts according to her/his best conditions and the provider (as follower) expected response function. The follower expected response function is characterized by the uncertain reaction of the follower to the different coordination/collaboration contracts offers at each time period over the discrete planning horizon, which is modeled as probability of acceptance. This uncertain reaction of the follower partner results from the uncertain behavior of its SC third parties. In this chapter, the uncertainty of the third parties price policies are considered when building the coordination/collaboration contracts, however, the SBDN approach is able to capture any uncertainty source that may affect the decentralized SC decision-making.

The SBDN negotiation outcome depends on the quality of the knowledge that the leader acquires about the follower SC and the market conditions. For example, good knowledge about i) the economic situation of the participants, especially at the standalone case, ii) the market conditions, iii) the main goals of enterprises stakeholders, iv) knowledge about third parties (e.g.: prices policies), v) uncertainty conditions and risk propensity of the participants, and finally vi) the willingness to collaborate (Figure 6.3). And since sharing knowledge is subjected to uncertainty, the proposed SBDN is built on the basis on incomplete information of the follower conditions.

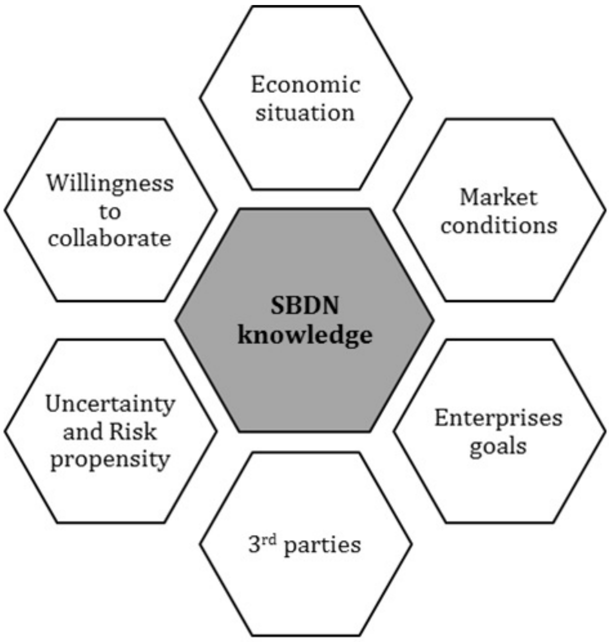


Figure 6.3: SBDN negotiation knowledge

The proposed SBDN methodology is built on win-to-win conditions. This means that information about the standalone profits of all participants is necessary in order to assess the coordination/collaboration agreement. This part is one of the added value of this chapter, as both negotiating partners SCs can operate as standalone production SCs, thus giving the follower partner flexibility to accept/reject the final coordination/collaboration agreement. Figure 6.4 summarizes the SBDN methodology, which is divided into two main parts: preparation of the coordination/collaboration contracts, and ii) assessing the coordination contracts and preparing the final agreement.

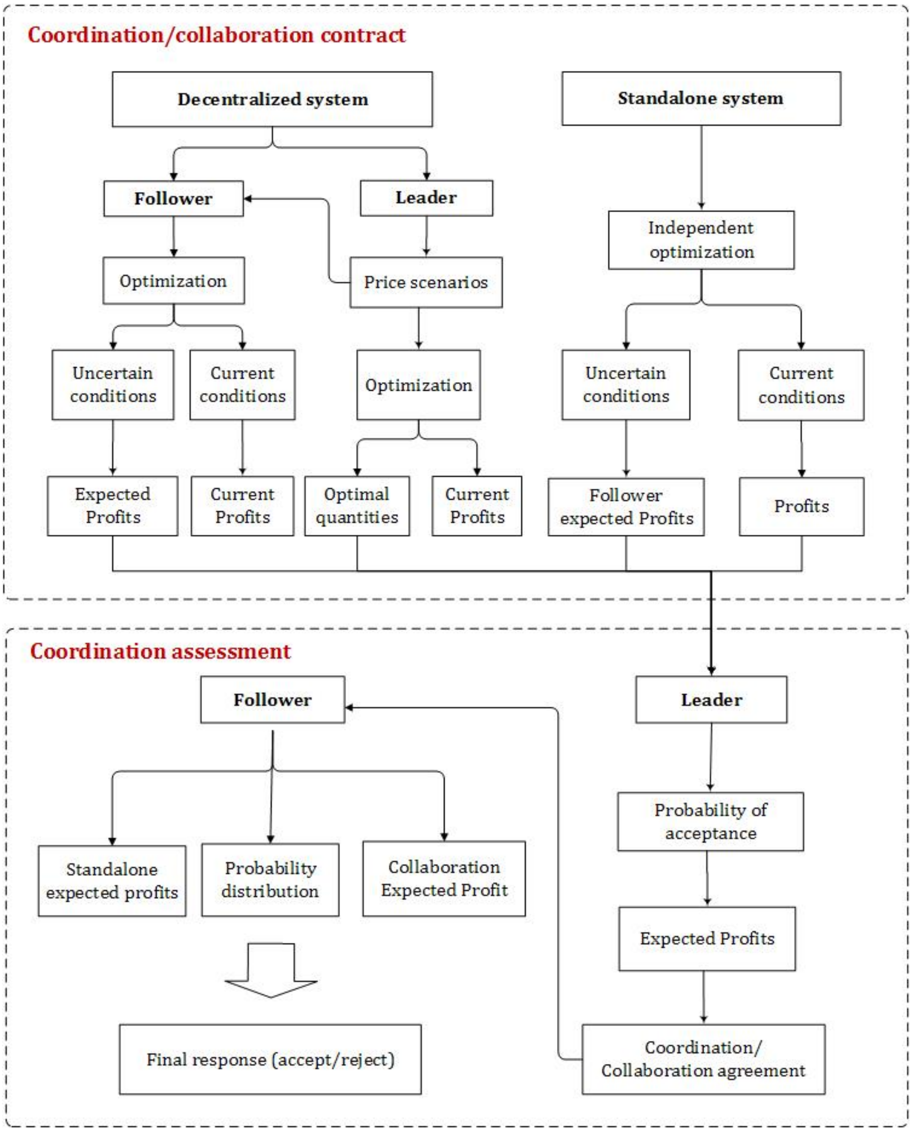


Figure 6.4: SBDN methodology flowchart

i) Coordination/collaboration contracts

Before starting the negotiations, both negotiating partners obtain their standalone profits to be used as benchmarks for the preparation and the assessment of the coordination/collaboration contracts. Then, the SBDN negotiation starts from the leader side. Based on dynamic "sequential" negotiations, the leader partner designs a set of possible coordination/collaboration contracts, resulting in a set of quantities and unit transfer prices for the inner component (negotiation elements) based on her/his optimal conditions. To do so, a set of prices are proposed based on the knowledge that the leader acquires about the competitive external clients (follower third parties) and external market conditions. Then, a set of optimal quantities over time is obtained and proposed to the follower partner together with their corresponding unit transfer prices. Both negotiating partners then optimize their SCs tactical models, individually, taking into consideration the bargaining flows (quantities vs. unit transfer price) over a discrete planning horizon.

In this step, the expected profits of the follower partner are obtained based on the coordination/collaboration contracts offers considering the uncertainty of the third parties' price policies. Monte-Carlo sampling method is used to generate a random set of scenarios for the uncertain sources, so that the follower profits scenarios can be obtained.

ii) Coordination/collaboration assessment

In this step, the proposed coordination/collaboration contracts offers are reduced to three to cope with the different decision-makers risk behaviors (risk seeking, risk neutral, or risk averse). The final coordination/collaboration contracts are assessed from each trading partner side as follows:

From the leader side:

The leader partner has to anticipate if the follower would accept each proposed coordination/collaboration contract offer taking into consideration the uncertain reaction associated with the follower external conditions. This uncertain reaction is modeled and quantified as probability of acceptance. Additionally to the incomplete knowledge that the leader partner knows about the follower external conditions, this probability of acceptance can be calculated considering a set of external feasible scenarios (follower SC) of the third parties price policies using the Monte-Carlo sampling approach. Then, this probability of acceptance function is considered to calculate the leader expected profits. The final coordination/collaboration agreement proposed by the leader partner will be the one that leads to the highest expected profit, which in turn depends on the risk behavior of the leader partner. In this thesis, the three coordination/collaboration agreements associated with all risk behaviors are analyzed and compared.

From the follower side:

On the basis of the proposed coordination agreements proposed by the leader partner, the follower assesses the risks associated with accepting or rejecting the offers, in comparison with the standalone case. The assessment step is based on the probability distribution of the follower profits scenarios resulted from the Monet-Carlo sampling method. It is worth mentioning that the follower assessment process does not consider the mean of the profits scenarios as the assessment reference, instead, the distribution of the values of these scenarios around the mean is considered. The final response depends also on how the follower partner manages uncertainty, which depends on the risk behavior of the decision-maker (risk-seeking, risk-neutral, or risk-averse).

6.3.2 Cooperative negotiation methodology

The cooperative negotiations in this chapter is similar to the coordination approach proposed in Chapter 4. The difference, as will be explained in the mathematical model, is that this cooperative approach is between the two main negotiating partners. The cooperative negotiation deals with the different enterprises SCs as one system, in which the negotiating partners decide to form a coalition towards maximizing the SC overall revenues from a global perspective. The results obtained from the non-cooperative SBDN will be compared with the cooperative and the standalone systems.

6.4 Mathematical formulations

A generic tactical coordinated MINLP model is developed to optimize the tactical decisions of a large-scale multi-enterprise multi-product SC from a decentralized perspective. The developed model is built to cope with the different systems (cooperative, non-cooperative SBDN, and standalone). The mathematical formulations are built to be flexible enough to incorporate, simultaneously, all possible participants within the boundaries of the SC of interest. The negotiating enterprises stakeholders participate with their respective complete SCs and third parties in the decentralized decision-making process. Furthermore, the model formulations allows the participants to play different roles (e.g.: a client for one enterprise and a provider for another enterprise) within a large-scale decentralized system.

To represent the negotiation methodology, a set of supply chains ($sc1$, $sc2...SC$) is considered in the mathematical model formulations linking each SC to its corresponding negotiation partner (leader L, follower F). Furthermore, a set of third parties D is considered (leader external providers xv, follower external clients xc, external suppliers s, and final customers m). All these third parties participate in the model formulations with their perspective price policies according to Chapter 5. The tactical model also includes a set of resources

r (raw materials and utilities, products, waste, etc.), production plants pl, and warehouses w. A subset r' is considered to represent the inner component resource (negotiation item). This negotiation item can be purchased from third parties (external providers xv), and/or sold to other third parties (external clients xc).

Figure 6.5 illustrates the main interaction terms between the leader and the follower SCs, including their third parties. $Q_{r',sc,t}$ represents the quantity of the negotiation resource r' delivered by the follower SC F each planning time period t at a unit transfer price $p_{r',sc}$. $FC_{r',sc,xc,t}$ represents the flows of the same kind of resource r' from the follower SC F to external clients xc at a unit price $pc_{r',xc,t}$. $VL_{r',xv,sc,t}$ corresponds to the resources r' flows provided by the external providers xv to the leader SC L at a unit price $pv_{r',xv,t}$.

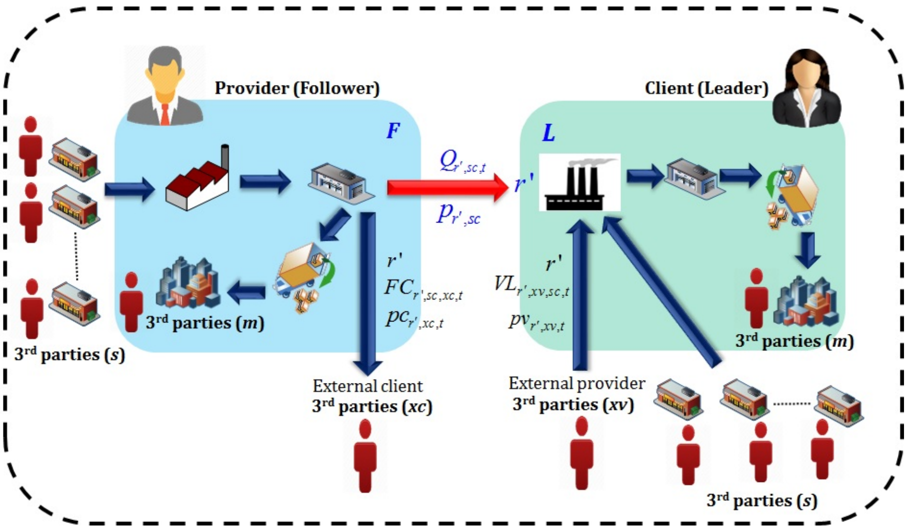


Figure 6.5: Variable interactions between participants

Eq. (6.1) represents the negotiation resource r' quantities demanded $QL_{r',pl,t}$ by the leader SC production plants pl. These quantities are equal or more than the resource r' production $FPD_{r,r',pl',sc,t}$ in the follower SC using resource r from third parties (external suppliers s) multiplied by a production factor $f_{r,r',sc}$ menus the quantities sold $FC_{r',sc,xc,t}$ to third parties (external clients xc) each planning time period t. This production factor depends on the utilized production recipe, assuming linear correlations.

$$\begin{aligned}\sum_{pl \in PL} QL_{r',pl,t} \geq & \sum_{\substack{sc \in F \\ sc \in SC}} \sum_{\substack{r \in R \\ r \neq r'}} \sum_{\substack{pl' \in PL \\ pl \neq pl'}} FPD_{r,r',pl',sc,t} \cdot f_{r,r',sc} \\ & - \sum_{\substack{sc \in F \\ xc \in D}} FC_{r',sc,xc,t} \qquad \forall r' \in R; t \in T\end{aligned} \tag{6.1}$$

Eq. (6.2) represents the resources $MK_{r,w,sc,m,t}$ flows from the warehouses w of the participating supply chains sc to third parties (final customers m)

$$\sum_{w \in W} MK_{r,w,sc,m,t} \leq xdem_{r,sc,m,t} \qquad \forall sc \in SC; r \in R; m \in D; t \in T \tag{6.2}$$

The negotiation item resource r' balance at the warehouses of the participating SCs is illustrated in Eq. (6.3). $ST_{r',w,sc,t}$ corresponds to the storage levels of r' at warehouse w of any of the negotiating partners SC at time t. The term $(\sum_{sc \in F} \sum_{pl \in PL} FPRO_{r',pl,sc,t} - \sum_{sc \in F} \sum_{w' \in W} Q_{r',w,sc,w',t} - \sum_{sc \in F} \sum_{xc \in D} C_{r',w,sc,xc,t})$ is considered to represent the mass balance of resource r' in the follower SC. $FPRO_{r',pl,sc,t}$ corresponds to the follower SC production levels of r' in the production plants pl each planning time period t. $Q_{r',w,sc,w',t}$ represents the quantity flows of r' from the warehouses w of the follower SC to the warehouses w' of the leader SC each planning time period t. $C_{r',w,sc,xc,t}$ represents the quantity flows of r' from the warehouses w of the follower SC to the external clients xc each planning time period t. The term $(\sum_{sc \in L} \sum_{w' \in W} Q_{r',w',w,sc,t} + \sum_{sc \in L} \sum_{xv \in D} V_{r',xv,w,sc,t} - \sum_{sc \in L} \sum_{r \in R} \sum_{pl \in PL} LPRO_{r',r,pl,sc,t} . fac_{r',r,sc})$ is considered when the SC belongs to the leader partner. $Q_{r',w',w,sc,t}$ corresponds to the quantity flows of r' at the warehouses w of the leader SC from the follower SC warehouses w' each time period t. $V_{r',xv,w,sc,t}$ represents the quantity of r' purchased from the external providers xv. $LPRO_{r',r,pl,sc,t}$ is the production levels of resource r (intermediate product, final product, etc.) from r' in the leader SC production plants pl each time period t, based on the production recipe represented by $fac_{r',r,sc}$, assuming linear correlations.

$$
\begin{aligned}
ST_{r',w,sc,t} + ST^{stock}_{r',w,sc,t} - ST_{r',w,sc,t-1} = & \sum_{sc \in F} \sum_{pl \in PL} FPRO_{r',pl,sc,t} \\
& - \sum_{sc \in F} \sum_{\substack{w' \in W \\ w' \neq w}} Q_{r',w,sc,w',t} - \sum_{sc \in F} \sum_{xc \in D} C_{r',w,sc,xc,t} \\
& + \sum_{sc \in L} \sum_{\substack{w' \in W \\ w' \neq w}} Q_{r',w',w,sc,t} + \sum_{sc \in L} \sum_{xv \in D} V_{r',xv,w,sc,t} \\
& - \sum_{sc \in L} \sum_{\substack{r \in R \\ r \neq r'}} \sum_{pl \in PL} LPRO_{r',r,pl,sc,t}.fac_{r',r,sc} \\
& \forall r \in R; sc \in SC; w \in W; t \in T
\end{aligned}
\tag{6.3}
$$

Here, it can be seen the the generality and the flexibility of the proposed model, as it allows all possible links between all possible participants, including the third parties. Furthermore, the proposed model formulations can be easily extended to consider the complete SC structure of the third parties, as will be seen in Chapter 7.

Eq. (6.4) and Eq. (6.5) illustrate the production and storage minimum and maximum capacities, respectively.

$$
PRO^{min}_{r,pl,sc,t} \leq PRO_{r,pl,sc,t} \leq PRO^{max}_{r,pl,sc,t} \qquad \forall r \in R; pl \in PL; sc \in SC; t \in T \tag{6.4}
$$

$$
ST^{min}_{r,w,sc,t} \leq ST_{r,w,sc,t} \leq ST^{max}_{r,w,sc,t} \qquad \forall r \in R; w \in W; sc \in SC; t \in T \tag{6.5}
$$

The objective function is to maximize the individual enterprises profits $PROF_{sc}$ (Eq. (6.6)), which is the difference between the individual economic sales and costs.

$$
PROF_{sc} = SALE_{sc} - COST_{sc} \qquad \forall sc \in SC \tag{6.6}
$$

The economic sales $SALE_{sc}$ (Eq. (6.7)) are equal to the sales to final customers m plus the sales to the leader partner SC L plus the sales to external clients xc.

$$SALE_{sc} = \sum_{r \in R} \sum_{w \in W} \sum_{m \in D} \sum_{t \in T} MK_{r,w,sc,m,t}.rp_{r,sc,m}$$
$$+ \sum_{sc \in F} \sum_{\substack{r' \in R \\ r' \neq r}} \sum_{t \in T} Q_{r',sc,t}.p_{r',sc} + \sum_{sc \in F} \sum_{\substack{r' \in R \\ r' \neq r}} \sum_{xc \in D} \sum_{t \in T} FC_{r',sc,xc,t}.pc_{r',xc,t} \quad (6.7)$$
$$\forall sc \in SC$$

The SC cost $COST_{sc}$ is obtained based on the external resources acquisition cost CRM_{sc}, production cost CPR_{sc}, storage cost CST_{sc}, distribution CTR_{sc}, negotiation resource cost ($\sum_{sc \in L} \sum_{r' \in R} \sum_{t \in T} Q_{r',sc,t}.p_{r',sc}$), and purchase cost from external providers ($\sum_{xv \in D} \sum_{sc \in L} \sum_{r' \in R} \sum_{t \in T} VL_{r',xv,sc,t}.pv_{r',xv,t}$) (Eq. (6.8)). Here, it can be noticed the conflict of interest resulting from the contrasting objectives between the negotiating partners, as the value of the negotiation resource ($Q_{r',sc,t}.p_{r',sc}$) is considered as a cost when the SC belongs to the leader (Eq. (6.8)) and as an income when the SC belongs to the follower partner (Eq. (6.7)). $Q_{r',sc,t}$ and $p_{r',sc}$ are the coordination/collaboration contract items, to be documented using the SBDN.

$$COST_{sc} = CRM_{sc} + CPR_{sc} + CST_{sc} + CTR_{sc}$$
$$+ \sum_{sc \in L} \sum_{r' \in R} \sum_{t \in T} Q_{r',sc,t}.p_{r',sc} + \sum_{r' \in R} \sum_{xv \in D} \sum_{sc \in L} \sum_{t \in T} VL_{r',xv,sc,t}.pv_{r',xv,t} \quad (6.8)$$
$$\forall sc \in SC$$

All third parties (external suppliers s, final customers m, external clients xc, and external providers xv) participate by their price policies considering the piecewise pricing model proposed in Chapter 5. For example, Eqs. ((6.9)-(6.14)) explain the integration of the external provider xv price policy in the mathematical model. Different price ranges n are offered by the external providers xv to the leader according to the quantity demanded each time period t, $VL_{r',xv,sc,t,n}$ and $pv_{r',xv,t,n}$ are the quantity purchased from the external providers xv by the leader SC and the unit price at each pricing zone n each time period t. $PE_{r',xv,sc,n}$ is the price elasticity of demand of the resource r' at each pricing zone n. The binary variable $y_{r',t,n}$ is used to allocate each purchase quantity $VL_{r',xv,sc,t}$ to its corresponding unit price $pv_{r',xv,t}$. The rest of the third parties are integrated using the same methodology.

$$y_{r',t,n}.VL^{min}_{r',xv,sc,t,n-1} \leq VL_{r',xv,sc,t,n} \leq y_{r',t,n}.VL^{max}_{r',xv,sc,t,n} \quad (6.9)$$
$$\forall r' \in R; sc \in L; xv \in D; t \in T; n \in N$$

$$y_{r',t,n}.pv^{min}_{r',xv,t,n} \leq pv_{r',xv,t,n} \leq y_{r',t,n}.pv^{max}_{r',xv,t,n-1} \quad \forall r' \in R; xv \in D; t \in T; n \in N \tag{6.10}$$

$$PE_{r',xv,sc,n} = \frac{\delta VL_{r',xv,sc,t,n}}{\delta pv_{r',xv,t,n}} \qquad \forall r' \in R; sc \in L; xv \in D; t \in T; n \in N \tag{6.11}$$

$$pv_{r',xv,t} = \sum_{n \in N} pv_{r',xv,t,n} \qquad \forall r' \in R; xv \in D; t \in T \tag{6.12}$$

$$VL_{r',xv,sc,t} = \sum_{n \in N} VL_{r',xv,sc,t,n} \qquad \forall r' \in R; sc \in L; xv \in D; t \in T \tag{6.13}$$

$$\sum_{n \in N} y_{r',xv,t,n} \leq 1 \qquad \forall r' \in R; xv \in D; t \in T \tag{6.14}$$

The external resources r acquisition cost CRM_{sc} from the external suppliers s is computed as in Eq. (6.15). $vrm_{r,s,sc,t}$ and $RM_{r,s,sc,t}$ correspond to the amounts and unit price of the external resources r purchased from suppliers s each time period t. Both values are computed using the same methodology as in Eqs. ((6.9) - (6.14)), with different price policy.

$$CRM_{sc} = \sum_{r \in R} \sum_{s \in D} \sum_{t \in T} vrm_{r,s,sc,t}.RM_{r,s,sc,t} \qquad \forall sc \in SC \tag{6.15}$$

The production cost CPR_{sc} is calculated as in Eq. (6.16). $FPRO_{r',pl,sc,t}$ and $uprdf_{r',sc}$ correspond to the production levels of resource r' in the follower SC each time period t and the unit production cost. $PRO_{r,pl,sc,t}$ and $upro_{r,sc}$ represent the production levels of resource r in each production plant pl each time period t and the unit production cost.

$$\begin{aligned} CPR_{sc} = & \sum_{sc \in SC} \sum_{pl \in PL} \sum_{r' \in R} \sum_{t \in T} FPRO_{r',pl,sc,t}.uprdf_{r',sc} \\ & + \sum_{r \in R} \sum_{pl \in PL} \sum_{t \in T} PRO_{r,pl,sc,t}.upro_{r,sc} \qquad \forall sc \in SC \end{aligned} \tag{6.16}$$

The storage cost CST_{sc} is computed as in Eq. (6.17) considering the unit storage costs $ustr_{r,w,sc}$ and $ust_{r',w,sc}$ of resources r and r', respectively. $STR_{r,w,sc,t}$ and $ST_{r',w,sc,t}$ correspond to the storage levels of resources r and r' each time period t, respectively.

$$CST_{sc} = \sum_{sc \in F} \sum_{r' \in R} \sum_{w \in W} \sum_{t \in T} ST_{r',w,sc,t}.ust_{r',w,sc}$$
$$+ \sum_{r \in R} \sum_{w \in W} \sum_{t \in T} STR_{r,w,sc,t}.ustr_{r,w,sc} \qquad \forall sc \in SC \tag{6.17}$$

The distribution cost CTR_{sc} (Eq. (6.18)) is computed based on the travel distances $df_{sc,w'}$ (between follower SC and leader warehouses w', $ds_{s,sc}$ (from external suppliers), and $dm_{m,sc}$ (to final customers) and their units transport costs $utrf_{r',sc}$, $utrs_{r,sc}$, and $utrm_{r,sc}$, respectively. It is assumed that the resource r' transport is on the expenses on the follower partner. The distribution costs of r' from external providers and to the external clients are considered on the expenses of their enterprises.

$$CTR_{sc} = \sum_{r' \in R} \sum_{t \in T} \sum_{w' \in W} \sum_{sc \in F} Q_{r',sc,w',t}.df_{sc,w'}.utrf_{r',sc}$$
$$+ \sum_{r \in R} \sum_{t \in T} \sum_{s \in D} RM_{r,s,sc,t}.ds_{s,sc}.utrs_{r,sc} \tag{6.18}$$
$$+ \sum_{r \in R} \sum_{t \in T} \sum_{m \in D} MK_{r,sc,m,t}.dm_{m,sc}.utrm_{r,sc} \qquad \forall sc \in SC$$

The above model formulations are generic enough that can be applied to standalone systems (by eliminating the resources interactions $Q_{r',sc,t}$). Furthermore, the proposed model can be extended/modified to cope with the cooperative systems by considering the overall profit as the objective function (Eq. (6.19))

$$Tprofit = \sum_{sc \in SC} PROF_{sc} \tag{6.19}$$

Uncertainty management

The leader partner has to anticipate the follower reaction to the different coordination contracts offers, which is subjected to uncertainty due to the uncertain nature of its third parties. The uncertain reaction of the follower partner is represented in the leader SC model as a probability of acceptance $prob_{sc}$ (Eq.

(6.20)). A Monte-Carlo sampling method is used to generate a random set of the third parties' price policies ($vrm_{r,s,sc,t}$, $rp_{r,sc,m}$, and $pc_{r',xc,t}$). The probability of acceptance is computed considering the frequency of the successful profits scenarios (NS_{sc}), in comparison with the standalone profits scenarios using the same generated scenarios. TN_{sc} is the total number of generated scenarios. The probability of acceptance thus reflects the variations among the different values of the profits scenarios, as the mean does not represent these variations. By doing so, the impact of each profit scenario is considered in the decentralized decision-making process.

$$prob_{sc} = \frac{NS_{sc}}{TN_{sc}} \qquad \forall sc \in F \tag{6.20}$$

Then, the leader expected profit $EXPROF_{sc}$ is obtained considering the probability of acceptance values (Eq. (6.21)). $PROF_{sc}$ corresponds to the leader profit if the follower accepts the coordination agreement, $SPROF_{sc}$ is the leader standalone profit (if the follower rejects the agreement).

$$EXPROF_{sc} = prob_{sc}.PROF_{sc} + (1 - prob_{sc}), SPROF_{sc} \qquad \forall sc \in L \tag{6.21}$$

The above model formulations result in different MINLP tactical models, which can be applied to different SC structures. It is flexible enough to capture all possible links among different participants, including third parties. The proposed model can be implemented to simple/complex SCs with centralized/decentralized decision-making considering cooperative, non-cooperative, and standalone systems. Incorporating the price policies of the third parties, regardless of the added complexity, allows them to participate in the decentralized decision-making, and thus control their financial nodes under different uncertain conditions. This incorporation may result in equilibrium between the external providers and the follower partner on one side, and between the external clients and the leader partner on the other side.

6.5 Case study

The proposed MINLP tactical models are implemented and solved for the case study extended from Chapter 5 in order to illustrate the proposed SBDN approach. Additionally, external providers and clients are added to the decentralized SC structure (Figure 6.6). The planning horizon is reduced from 10 to 6 time periods, and the capacity of each energy generation plant is increased from 5MWe to 6MWe in order to reflect the competitive pressure among partners, as the energy generation SC here is not the only energy provider to the polystyrene production SC.

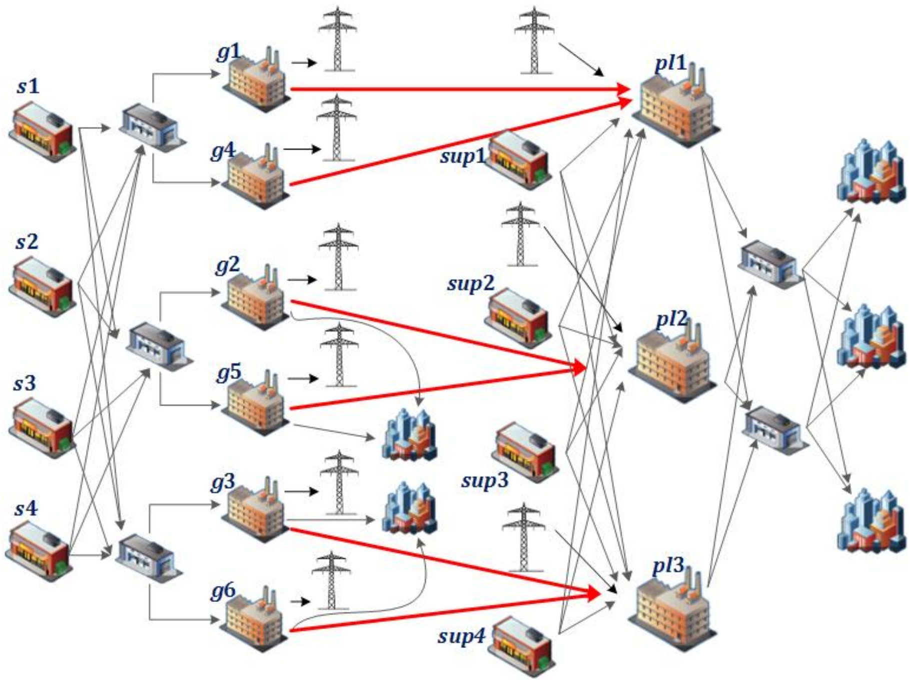


Figure 6.6: Global SC network

The negotiating partners are the polystyrene production SC organization (as leader) and the energy generation SC organization (as follower) (Figure 6.7). The internal energy is considered as the negotiation item to be agreed (quantities and price). Each negotiating partner owns independent SC with its own providers and clients. The polystyrene SC receives energy from the follower SC and from the electricity local grid (as external provider). The energy generation SC sells energy to the leader SC, external markets and the local grid (as external client). This gives the negotiating partners more flexibility to assess the negotiation outcome, especially the follower partner, as it is not obliged to collaborate.

Table 6.1 illustrates the external energy prices from and to the global SC network. These prices are according to the Spanish public electricity tariffs (Ministry of Industry, Energy and Tourism, 2015).

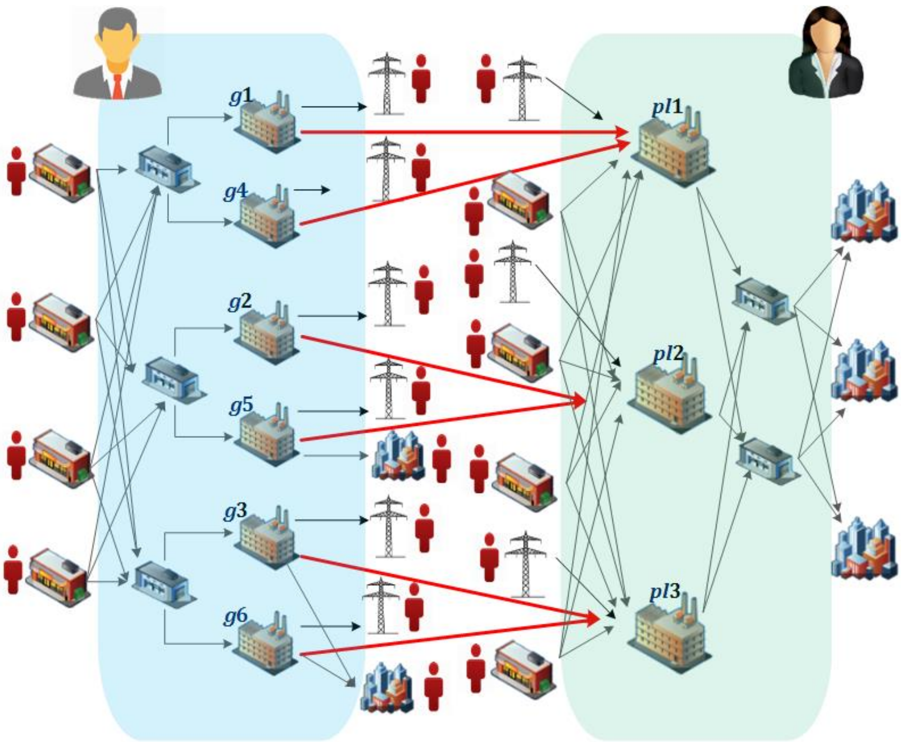


Figure 6.7: Decentralized SC stakeholders

Table 6.1: Nominal energy prices

	Price (m.u./kWh)
Energy price to external markets	0.20
Energy price to local grid (demand <2GWh per time period)	0.21
Energy price to local grid (2GWh<demand< 4GWh per time period)	0.20
Energy price to local grid (4GWh<demand < 6GWh per tine period)	0.19
Local grid energy price to external markets	0.22
Local grid energy price to polystyrene production SC (demand>2GWh per time period)	0.22
Local grid energy price to polystyrene production SC (2GWh<demand<4GWh per time period)	0.21
Local grid energy price to polystyrene production SC (4GWh<demand<8GWh per time period)	0.20

6.5.1 Monte-Carlo Sampling

Monte-Carlo sampling method is used, as part of the optimization process, in order to obtain the probability of acceptance of the different coordination/collaboration contracts and the probability distribution of the follower profits scenarios. To do so, the developed MINLP tactical model of the follower partner SC is solved for each coordination/collaboration contract considering the generated scenarios. A set of random scenarios (500 scenarios) is generated for each energy price policy of each participating third party around the follower partner SC, as follows:

(a) Local grid energy price to external markets (Figure 6.8).

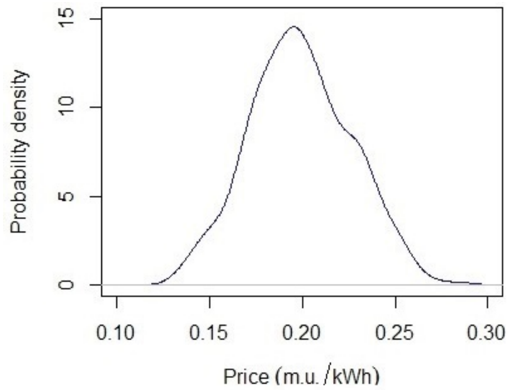


Figure 6.8: Probability density (a)

(b) Renewable energy price to the local grid, price zone 1 (Figure 6.9).

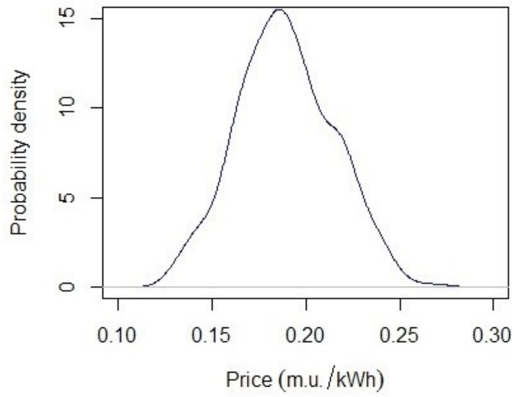


Figure 6.9: Probability density (b)

(c) Renewable energy price to the local grid, price zone 2 (Figure 6.10).

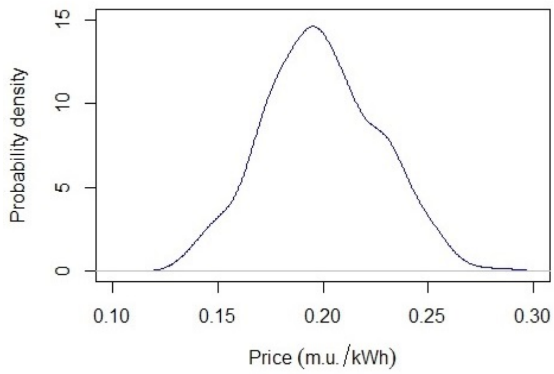


Figure 6.10: Probability density (c)

(d) Renewable energy price to the local grid, price zone 3 (Figure 6.11).

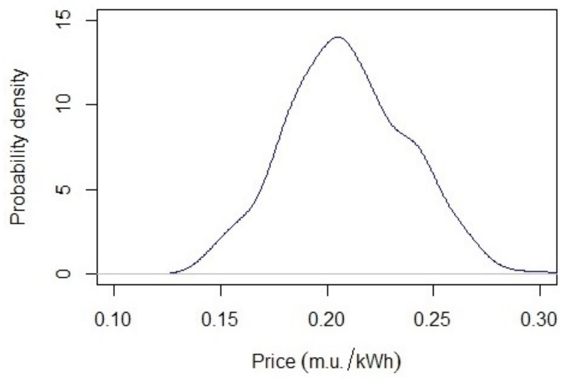


Figure 6.11: Probability density (d)

(e) Renewable energy price to the external markets (Figure 6.12).

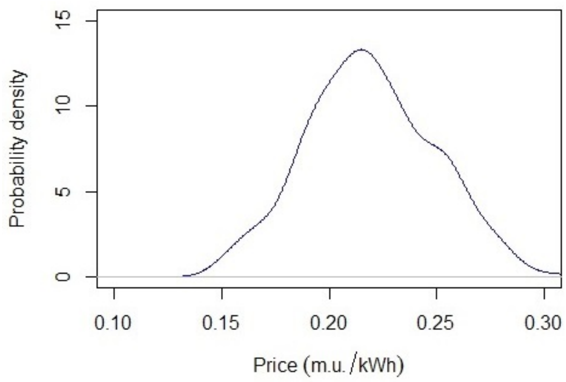


Figure 6.12: Probability density (e)

The prices scenarios are generated based on a normal distribution function (Figures 6.8-6.12), with standard deviation (σ = 0.03 m.u./kWh) for all price policies, and a mean (μ) equal to the current nominal prices as in Table 6.1. When solving the follower SC tactical model for this huge number of prices scenarios, the first normal distribution is generated (Figure 6.8), and then the remainder normal distributions are generated considering that they are correlated with the first one. The variations in the generated price scenarios can be justified by the volatile changes in the energy prices. So, their prediction depends on the perception of the volatile market prices by the leader decision-maker, and obviously, these predictions significantly affect the results of the presented case study. So, from these generated scenarios, the corresponding follower reactions are anticipated, so the leader SC expected profits can be obtained.

6.6 Results and discussions

The resulting MINLP tactical models are implemented on the General Algebraic Modeling System GAMS 24.2.3, and solved for 6 time periods; 1000 working hours each, using the Global mixed-integer quadratic optimizer "GloMIQO" (Misener & Floudas, 2013). A Windows 7 computer with an Intel Core$^{\mathrm{TM}}$ i7-2600 CPU 3.40 GHz processor with 16.0 GB of RAM is used.

6.6.1 Cooperative vs. non-cooperative systems

The individual tactical models are solved based on the current nominal energy prices (Table 6.1) considering the standalone, cooperative and non-cooperative systems. From the leader side, several prices (contract prices) are offered for the internal energy in the range [0.14-0.20] m.u./kWh. These prices depend on the knowledge that the leader acquires about the follower SC external energy prices (renewable energy price to local grid, local grid energy price to external markets, and renewable energy price to external markets) and market conditions. Indeed, the leader may offer lower prices than 0.14 m.u./kWh, but this contract would not be accepted by the follower partner.

The individual and the overall nominal profits are obtained (Figures 6.13, 6.14 and 6.15). The non-cooperative models are solved as described before. The dotted lines on the figures describe the standalone nominal profits of the leader (Figure 6.13) and the follower (Figure 6.14), as their collaboration makes sense when their individual profits exceed these lines.

From the leader side, Figure 6.13 shows that the non-cooperative system results in higher individual profits than the cooperative one at all the considered contract price offers, although the cooperative system leads to higher overall profits (Figure 6.15).

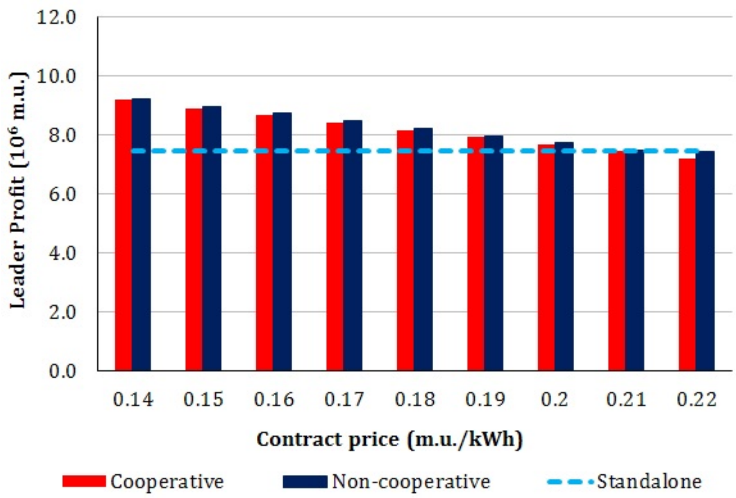


Figure 6.13: Leader nominal profits

From the follower side, Figure (6.14) illustrates that the cooperative system would lead to better solutions at contract price offers above 0.17 m.u./kWh, at the nominal situation, without considering its external uncertain conditions.

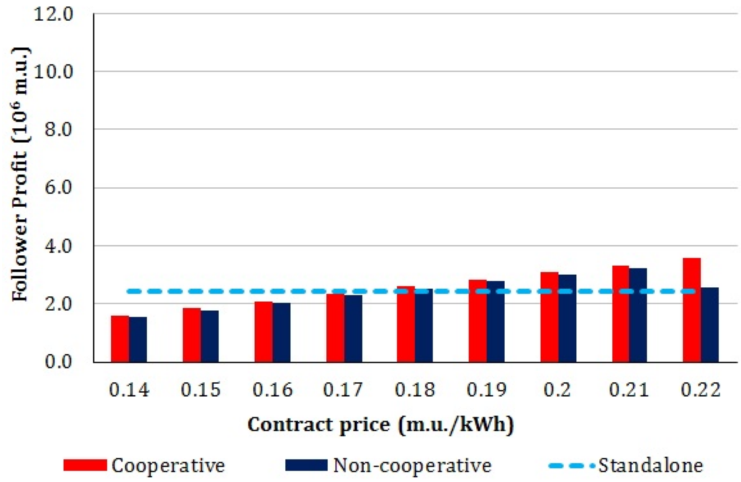


Figure 6.14: Follower nominal profits

It is noticed in Figure (6.15) that the non-cooperative total profit decreases at contract price 0.22 m.u./kWh, as the leader decision is to purchase most of the energy from the local grid, returning to the standalone case.

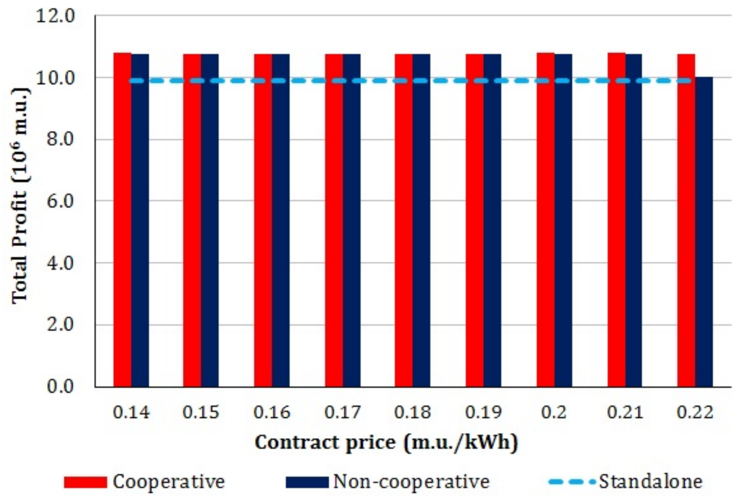


Figure 6.15: Total nominal profits

Furthermore, the mathematical formulation of the non-cooperative system is less complex, as it leads to better solutions in 32% and 63% less computational time, in comparison with the standalone and the cooperative systems, respectively (Table 6.2). This is because the follower individual model is solved based on fixing the transfer price offered by the leader partner, so fixing this degree of freedom variable leads to less computational efforts. The CPU times in the table are the summation fo both the CPU of the leader and the follower partners.

Table 6.2: Models statistics

	Single equations	Single variables	Discrete variables	CPU (sec)
Standalone	2,166	2,942	306	15.6
Cooperative	2,165	2,926	306	31.6
Non-cooperative	2,166	2,942	306	11.8

6.6.2 Coordination contract agreement

Based on the non-cooperative SBDN negotiation, the leader partner aims to reduce the aforementioned contract price offers by anticipating the follower uncertain reaction. To do so, the probability of acceptance of each coordination/collaboration contract offer is computed (Table 6.3) taking into consideration the follower expected profits resulting from the Monte-Carlo sampling method. The successful scenarios are the number of scenarios of favorable profit, in comparison with the standalone profit scenarios. It is noticed that the probability of acceptance is 0% for the contract prices less than 0.16 m.u./kWh, while it increases as the contract price increases, up to 100% at contract price 0.22 m.u./kWh (see Figure 6.16).

Table 6.3: Probability of acceptance

	0.14	0.15	0.16	0.17	0.18	0.19	0.20	0.21	0.22
No. of successful scenarios	0	0	0	89	314	393	440	477	498
Probability of Acceptance	0%	0%	0%	18%	63%	79%	88%	95%	100%

Then, based on the probability of acceptance values, the leader estimates its SC expected profit (Eq. (6.21)) for each contract offer considering the nominal profits (in case of the follower acceptance) and the standalone profits (Table 6.4). The best coordination/collaboration contract agreement results from purchasing 24.71 GWh (all the energy amounts needed for polystyrene production) from the follower partner.

It is noticed that at contract price 0.22 m.u./kWh, the decision for the leader partner is to purchase all the energy needed (24.71 GWh) from the local grid at energy prices in the range of [0.20-0.22] m.u./kWh (Table 6.1), returning to the standalone case.

Table 6.4: Coordination contracts from the leader side

Contract price (m.u./kWh)	Contract energy (GWh)	Grid energy (GWh)	Nominal profit (if accepted) (10^6m.u.)	Standalone profit (10^6m.u.)	Probability of acceptance	Expected profit (10^6m.u.)
0.14	24.71	0	9.25	7.47	0%	7.47
0.15	24.71	0	8.99	7.47	0%	7.47
0.16	24.71	0	8.74	7.47	0%	7.47
0.17	24.71	0	8.48	7.47	18%	7.65
0.18	24.71	0	8.23	7.47	63%	7.95
0.19	24.71	0	7.99	7.47	79%	7.88
0.20	24.71	0	7.77	7.47	88%	7.74
0.21	24.71	0	7.51	7.47	95%	7.50
0.22	0	24.71	7.47	7.47	100%	7.47

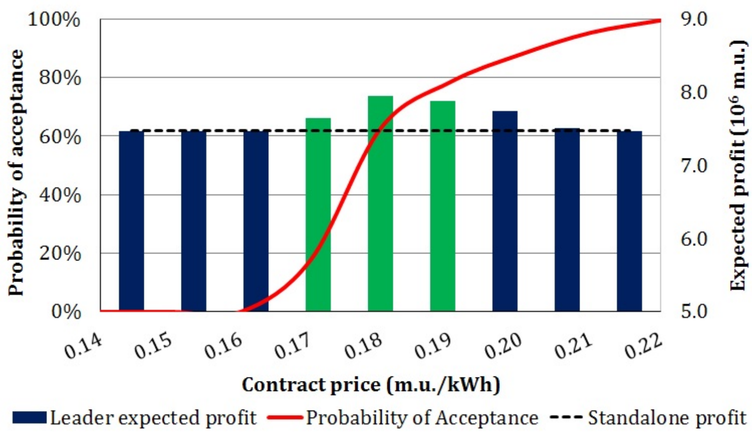


Figure 6.16: Leader expected profit vs probability of acceptance

The results reveal the impact of the local grid (as external provider "third party") energy price policy on the selection of coordination contract. For example, the local grid offers different price possibilities to the leader according to specific energy supplied each planning time period (see Table 6.1). So, it is better for the leader to maintain the coordination/collaboration contract with the follower, as the last does not impose any energy constraints (within its SC generation capacities). For example, Table 6.5 illustrates the contracted supply schedule of the contract energy amounts at unit price 0.21 m.u./kWh along the 6 planning periods. Purchasing 24.71 GWh from the follower (the summation of the energy amounts in Table 6.5) at contract price 0.21 m.u./kWh costs the leader partner 5.19x10^6 m.u. However, purchasing the same amounts from the local grid, considering the energy amounts constraints, results in 5.38x10^6 m.u. cost.

Table 6.5: Contract energy (price 0.21 m.u./kWh)

	Energy (GWh)					
Energy generation plants	t1	t2	t3	t4	t5	t6
g1	1.47	1.47	1.59	1.47	0.75	1.47
g2	2.56	1.53	2.56	1.53	0.95	1.31
g3	1.53	0.67	1.53	0.67	0.67	0.98

However, the coordination/collaboration contract proposed depends on the quality of the knowledge that the leader acquires about the follower partner and her/his perception about the external market conditions. So, within the context of the proposed SBDN methodology, the leader expected profit (based on the probability of acceptance) is considered as the main criterion for selecting the final coordination contract proposed. Other criteria may lead to different coordination contracts.

The selection of the coordination contract depends on the risk-behavior of the leader decision-maker. For example, if the leader offers prices 0.14-0.16 m.u./kWh, this would lead to 0% probability of acceptance resulting from the high frequency of the follower negative profits scenarios. This means that the leader decision-maker is not advised to chose the coordination contracts of the highest nominal profits. On the other side, selecting higher prices with higher probability of acceptance is neither advised, since this decision might not be profitable for the leader. For example, for the presented case study, if the leader decision-maker is risk-averse, she/he would offer the coordination contract (24.71 GWh at price 0.21 m.u./kWh) with 95% probability of acceptance; this decision leads to very low profits (0.5% higher than the standalone profit) .

Finally, from the leader side, the coordination contracts agreement (24.71 GWh at prices 0.17-0.19 m.u/kWh) are the best leader offers with the highest expected profits. Most of the reviewed literature tempts to assume a risk behavior of any/all the negotiating partners, however, in this chapter, different coordination contracts are proposed to cope with the different decision-makers risk behaviors, as follows:

Risk-seeking strategy

If the leader decision-maker is a risk-seeker, she/he would offer to purchase 24.71 GWh at contract price 0.17 m.u./kWh, taking into consideration the 18% probability of acceptance. This coordination contract leads to 8.48x10^6 m.u. nominal profit (if the follower accepts); 14% higher than the standalone nominal profit.

Risk-neutral strategy

If the leader is a risk-neutral, her/his strategy would be to purchase 24.71 GWh at 0.18 m.u./kWh, considering that this contract leads to 63% follower successful profits scenarios. This strategy results in 10 % leader pofits improvements (8.23x10^6 m.u), in comparison with the standalone nominal profit. This coordination contract leads to the highest leader expected profit (7.95x10^6 m.u.).

Risk-averse strategy

Here, the leader would offer the coordination contract (24.71 GWh at 0.19 m.u./kWh), resulting in 7.99x10^6 m.u nominal profit (7% higher than the standalone profit). The leader would offer this collaboration/coordination contract taking into consideration the follower high probability of acceptance (79%)

6.6.3 Negotiation outcome assessment

The follower partner is supposed to receive one coordination contract proposed. In this thesis, the three aforementioned coordination contracts are assessed by the follower partner, depending on how risky the organization is. To do so, the follower expected profits are obtained considering the successful scenarios (Table 6.6).

Table 6.6: Follower expected profit vs. coordination contracts

Contract price (m.u./kWh)	contract amount (GWh)	Successful profits probability	Expected profit (x10^6 m.u.)	Standalone expected profit (x10^6 m.u.)
0.17	24.71	18%	2.46	2.73
0.18	24.71	63%	2.71	2.73
0.19	24.71	79%	2.95	2.73

The cumulative expected profit probability of the follower resulting from accepting the collaboration/coordination contracts (0.17-0.19 m.u/kWh) are obtained, in comparison with the standalone case (dotted curves in Figures 6.17, 6.18 and 6.19. The response of the follower (accept/reject) to the leader offer depends to a high extent on her/his risk behavior, as follows:

Risk-seeking response

If the follower has a risk-seeking behavior, the response is likely to accept the contract price 0.17 m.u./kWh (amount 24.71 GWh) considering the 18% successful profits scenarios. As shown in Figure 6.17, the follower has a probability to gain more than 4x10^6 m.u. by accepting this offer, in comparison with the standalone profits scenarios. The expected profit (mean) of the 18 % successful profit scenarios lead to an expected profit 22% higher than the standalone expected profit for the same scenarios.

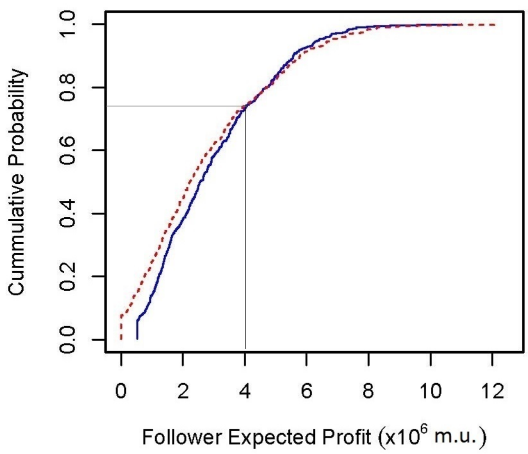


Figure 6.17: Follower expected profit cumulative probabilities for contracts around 0.17 m.u./kWh

Risk-neutral response

If the follower is a risk-neutral, the decision will be probably to accept the coordination/collaboration contract (24.71 GWh at price 0.18 m.u./kWh). Indeed, this response compensates the follower decision-maker, as 63% of the profits scenarios are successful (see Table 6.6) with higher frequencies (Figure 6.18), in comparison with the standalone profits scenarios. Furthermore, the expected profit (mean) of the 63% successful scenarios is 12% more than the expected standalone profit of the same scenarios. It is noticed from (Figure 6.18) that the cumulative probabilities of the follower profits if accepting the offer are high comparing with the standalone profits scenarios probabilities.

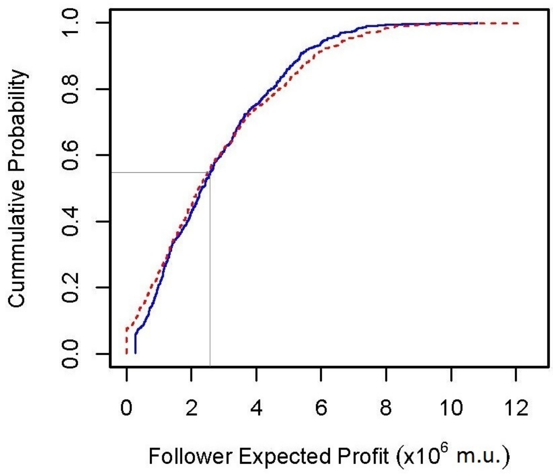


Figure 6.18: Follower expected profit cumulative probabilities for contracts around 0.18 m.u./kWh

Risk-averse response

The risk-averse behavior of the follower would lead to accept the contract offer (24.71 GWh at price 0.19 m.u./kWh), as 79% (393 of the 500 profits) scenarios are successful with higher frequencies (Figure 6.19) in comparison with the standalone profits scenarios. Moreover, the expected profit of the successful scenarios leads to 19% more gains than the standalone expected profit of the same scenarios.

Finally, it can be seen in Figures 6.17, 6.18 and 6.19 that increasing the contract price by 0.01 m.u./kWh leads to a potential increase in the follower expected successful profit cumulative probabilities.

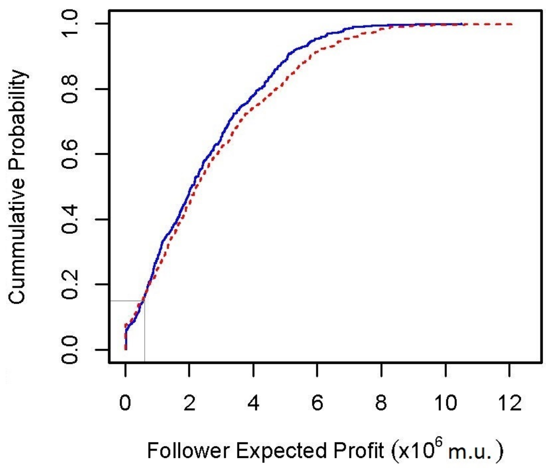
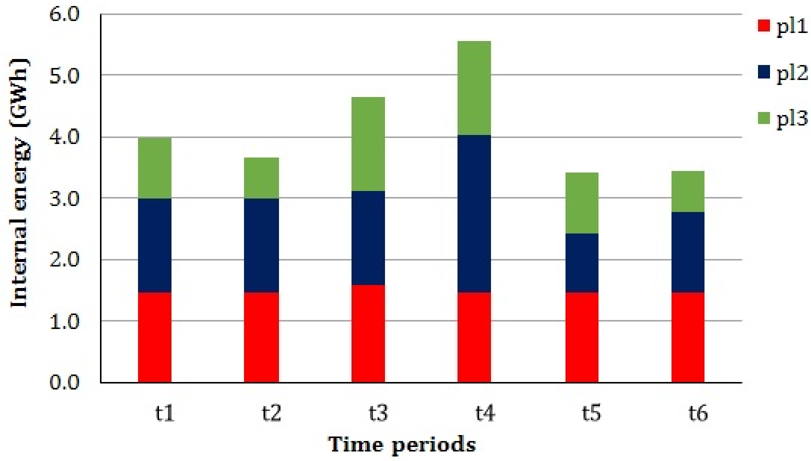


Figure 6.19: Follower expected profit cumulative probabilities for contracts around 0.19 m.u./kWh

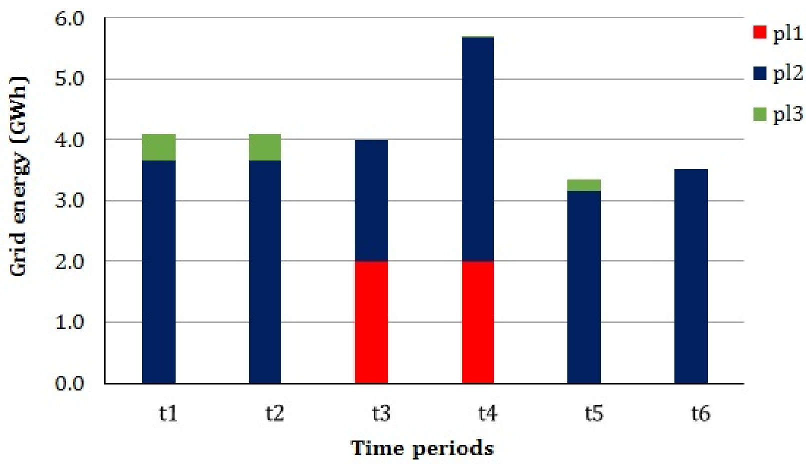
6.7 Results: Tactical decision-making

The effect of the coordination/collaboration resulted from the non-cooperative SBDN on the decentralized tactical decision-making is analyzed and compared with the standalone case. The tactical decisions obtained are the RMs purchase levels and the corresponding unit prices, internal energy (negotiation resource) flows and the unit transfer price, sales to markets and unit retail prices, storage, production and distribution levels over the 6 planning time periods.

The internal energy flows to the leader SC production plants resulted from the coordination/collaboration contract (24.71 GWh at 0.17 m.u./kWh) in comparison with the standalone case are illustrated in Figure 6.20. It is noticed that the coordination contract results in purchasing all the energy needed for the polystyrene production (24.71 GWh) from the follower partner. The polystyrene production plant *pl*2 dominates the internal energy orders from the follower SC; 38% of the total energy demand (Figure 6.20(a)). However, at the standalone case, all energy needed for the polystyrene production is purchased from the local grid. The trend of the standalone system is to order high amounts of energy from the local grid along the planning time periods in order to get lower prices (0.20-0.22 m.u./kWh). This leads to overload the polystyrene production plant *pl*2, while closing the polystyrene production plants *pl*1 and *pl*3 at several time periods (Figure 6.20(b)). In both cases, the total energy purchase amount is the highest at time period *t*4 in order to cope with the high polystyrene customers' demand at this tine period.



(a) 0.17 m.u./kWh

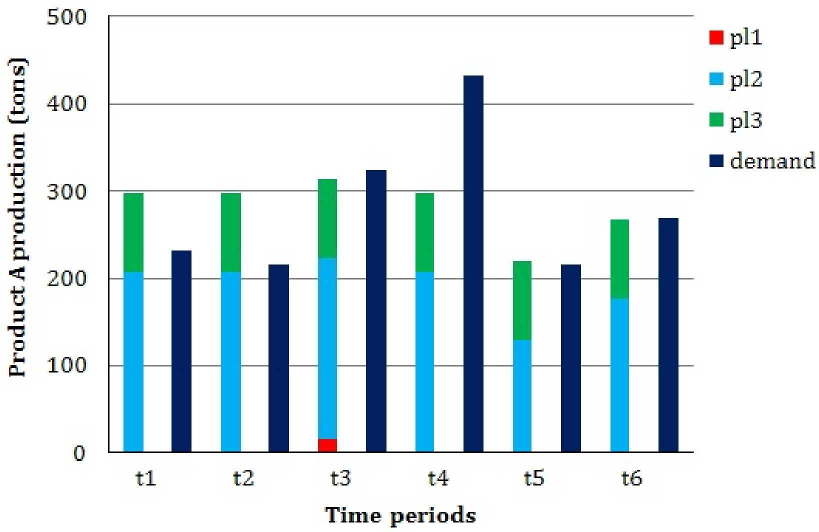


(b) Standalone

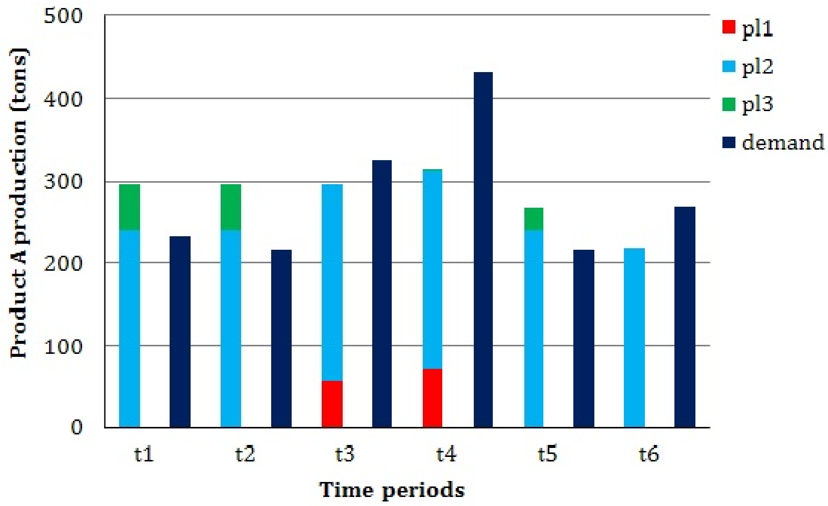
Figure 6.20: Internal energy amounts (coordination vs. standalone)

Figures 6.21 and 6.22 show how the coordination affects the polystyrene production activities, in comparison with the standalone case. Although the total production is the same in both cases, the coordination results in operating the polystyrene production plants all time periods (Figures 6.21(a) and 6.22(a)) to follow the internal energy orders. This leads to expand the distribution links resulting in higher distribution activities (Table 6.7). On th other side, at the standalone case, the polystyrene production at time period $t2$ exceeds the customer demand (Figures 6.21(b) and 6.22(b)), in which the excess products will be stored for later distribution. This explains the high storage amounts of the leader SC at the standalone case (Table 6.7).

Figure 6.21 shows the polystyrene production activities of product A. The coordination leads to operate the polystyrene production plant $pl2$ to produce 67% (1,134 tons) of the total product A demand, comparing with 84% (1,419 tons) using the standalone system. This difference is due to the different energy purchase orders along the planning time periods (see Figure 6.20). As explained before, the polystyrene production plant $pl2$ is the closest to the resource $rm2$ supplier $sup2$, which dominates the RM purchase orders (49% of the total RM purchase amounts).



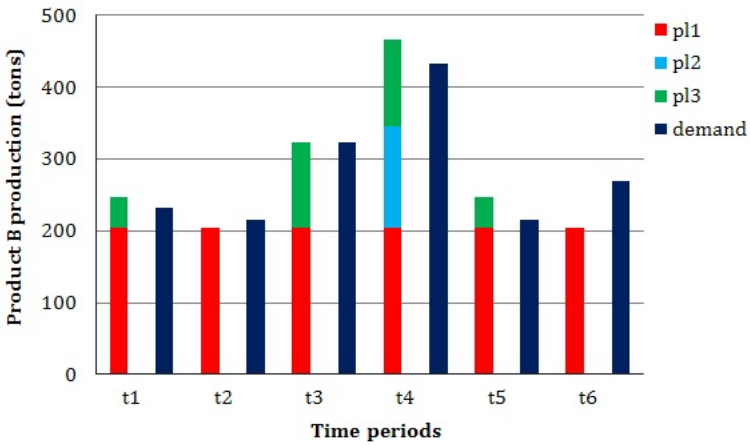
(a) 0.17 m.u./kWh



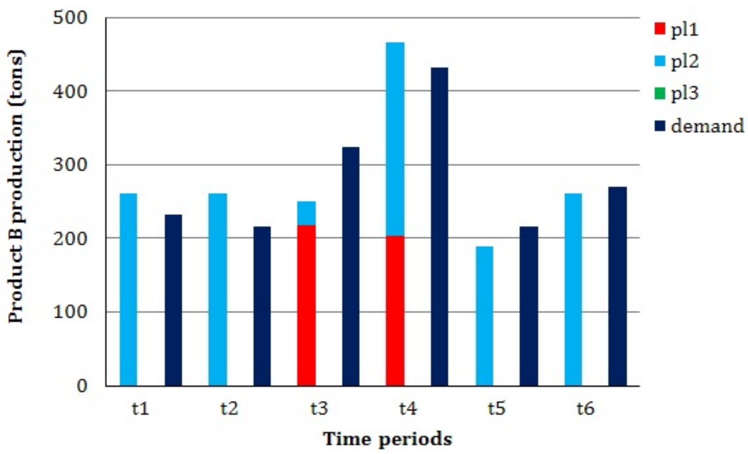
(b) Standalone

Figure 6.21: Polystyrene production levels (product A)

To produce product B, the coordination leads to operate the polystyrene production plant $pl1$ to produce 72% of the total production levels (Figure 6.22(a)). This also can be explained by its short distance to the resource $rm4$ supplier location, which dominates the rm supply for product B. However, at the standalone case, the polystyrene production plant $pl2$ dominates producing product B (Figure 6.22(b)), as it is close to the $rm3$ supplier, which dominates the RM supply (see Figure 6.23).

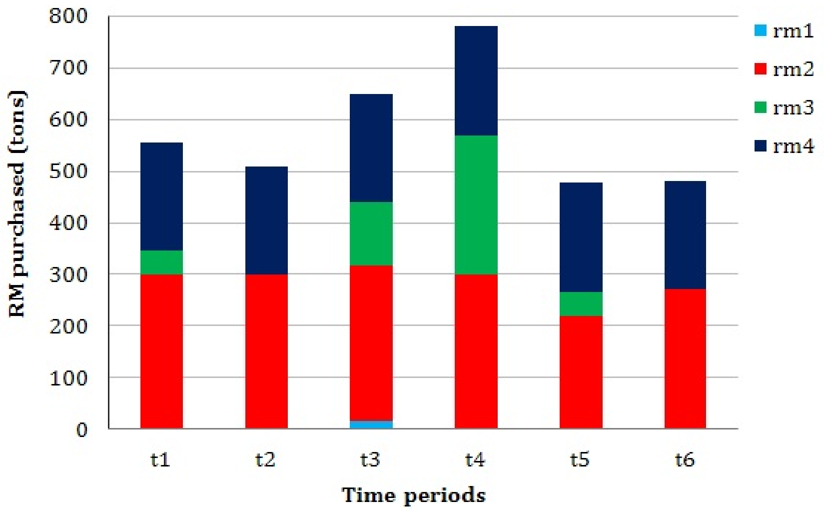


(a) 0.17 m.u./kWh

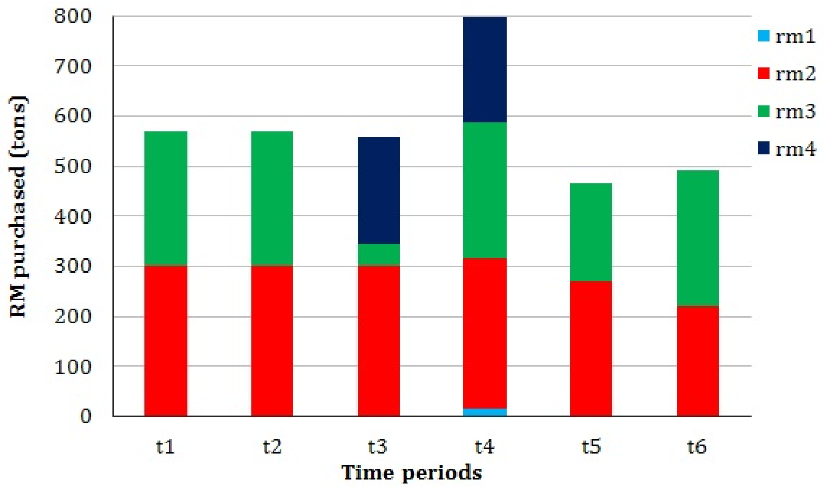


(b) Standalone

Figure 6.22: Polystyrene production levels (product B)



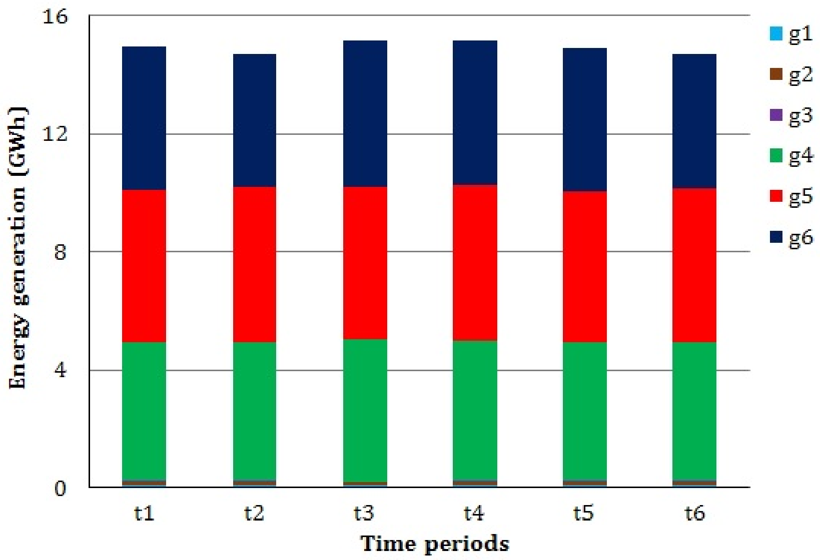
(a) 0.17 m.u./kWh



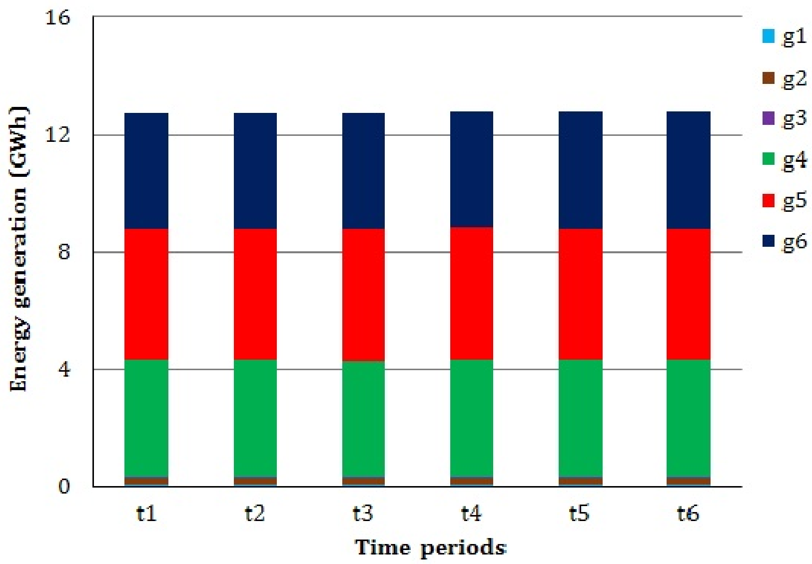
(b) Standalone

Figure 6.23: Leader RM purchase levels

The follower tactical decisions are also affected by the coordination contract. For example, Figure 6.24 illustrates the expected energy generation levels of the follower SC using the coordination/collaboration contract (24.71 GWh at 0.17 m.u/kWh), in comparison with the standalone case. The coordination contract results in equal distribution of energy generation activities among the renewable energy generation plants (Figure 6.24(a)) with a total generation of 15 GWh per time period; 15% more than the standalone expected energy generation per time (Figure 6.24(b)). This increase in the energy generation is due to the internal energy orders (24.71 GWh) according to the coordination contract, resulting in 18% increase in the expected RM purchase amounts, in comparison with the standalone expected amounts. The coordination also results in reductions in the expected energy sales to the local grid and the external markets.



(a) 0.17 m.u./kWh



(b) Standalone

Figure 6.24: Follower SC expected energy generation

6.7.1 Leader decisions-breakdown

The leader tactical/economic total decisions are analyzed and compared for the proposed coordination contracts considering the different risk strategies (risk-seeking, risk-neutral, and risk-averse). Table 6.7 summarizes the tactical decisions-breakdown of the different proposed coordination contracts, in comparison with the standalone case. It is noticed that the RM purchase and polystyrene production amounts are the same for all cases; 3,450 tons and 3,380 tons, respectively, but with different orders along the planning time periods. It is noticed that the coordination contracts result in 7-13% lower storage levels, and 4-5% higher distribution levels, in comparison with the standalone case. At the standalone case, the leader has to purchase high amounts of energy from the local grid in order to get lower prices resulting in peak productions.

Table 6.7: Leader tactical decisions-breakdown

	Contract price (0.17 m.u./kWh)	Contract price (0.18 m.u./kWh)	Contract price (0.19 m.u./kWh)	Standalone
RM purchase (tons)	3,449.75	3,449.75	3,449.75	3,449.75
Energy from grid (GWh)	0	0	0	24.71
Contract Energy (GWh)	24.71	24.71	24.71	0
Production (tons)	3,380.40	3,380.40	3,380.40	3,380.40
Distribution (k.tons.km)	1,328.19	1,332.07	1,328.19	1,271.50
Storage (tons.h)	468.90	495.00	468.90	530.18

Consequently, the selection of the coordination contract affects the economic decisions of the leader decision-maker (Figure 6.25). In the presented case study, the coordination/collaboration contracts 0.17, 0.18 , 0.19 m.u./kWh lead to $1x10^6$ m.u., $0.75x10^6$ m.u., and $0.51x10^6$ m.u savings in the energy purchase costs; 24%, 17%, and 11%, respectively, in comparison with the standalone case. Furthermore, these coordination/collaboration contracts result in $26x10^3$ m.u. and $42x10^3$ m.u. savings in the RM purchase and polystyrene production costs, in comparison with the standalone case.

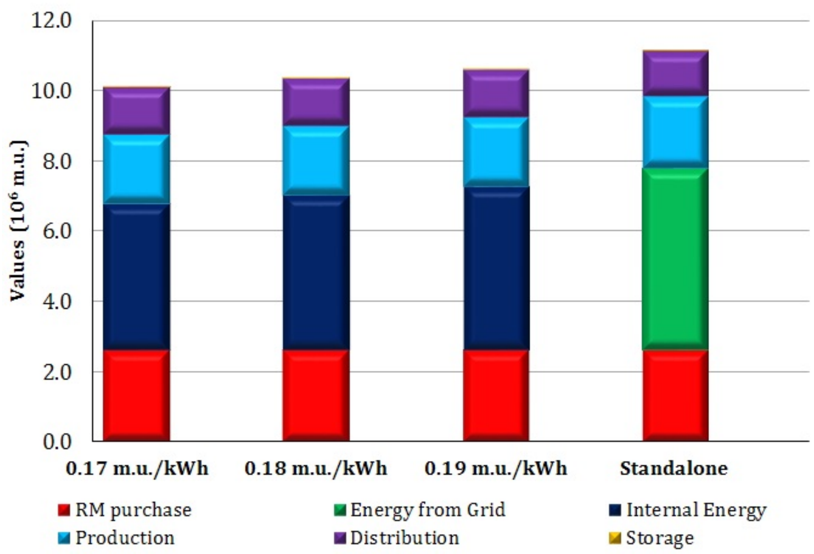


Figure 6.25: Leader economic decisions

Table 6.8 summarizes the final economic decisions of the leader partner resulted from the different coordination contracts, in comparison with the standalone case. As the decision is to fulfill the final customer demand, the total economic sales are the same in all cases (18.59x10^6 m.u.). However, the coordination contracts 0.17, 0.18, amd 0.19 m.u./kWh result in 14%, 10%, and 7% improvements in the leader profits, respectively, comparing with the standalone case.

Table 6.8: Leader economic summary

	Contract price (0.17 m.u./kWh)	Contract price (0.18 m.u./kWh)	Contract price (0.19 m.u./kWh)	Standalone
Cost (x10^6 m.u.)	10.11	10.36	10.61	11.12
Sales (x10^6 m.u.)	18.59	18.59	18.59	18.59
Profit (x10^6 m.u.)	8.48	8.23	7.99	7.47

6.7.2 Follower expected decisions-breakdown

Figure 6.26 summarizes the economic decisions of the follower partner using the different coordination contracts, in comparison with the standalone case. As mentioned before, the coordination results in 15% increase in the expected energy generation, which in turn leads to 16.5% reductions in the expected economic energy sales to third parties (local grid and external markets). Unlike what is expected, the follower partner could not sell more energy to third parties to compensate these reductions, as the corresponding cost is high; generating 1% more energy leads to 1% increase in the follower SC expected cost. The coordination results in 14% increase in the expected energy generation cost, ensuing in 16% increase in the RM purchase cost.

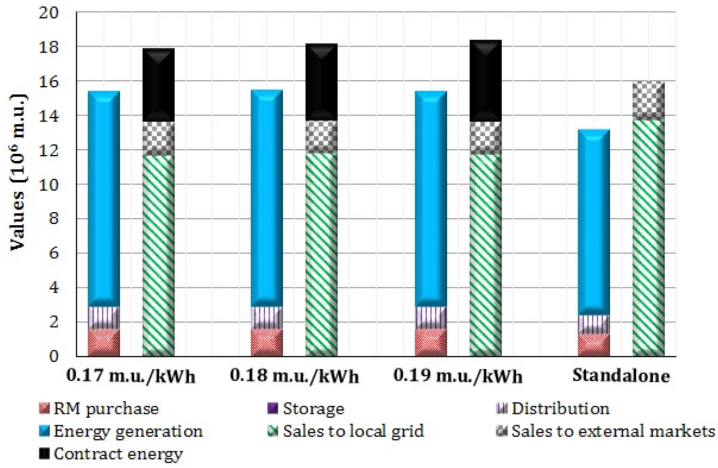


Figure 6.26: Follower expected economic decisions

Table 6.9 summarizes the consequences of the follower expected decisions resulting from the different coordination contracts proposed, in comparison with the consequences associated to the expected standalone decisions. Their values are obtained after solving the follower model for external prices generated using the same Monte- Carlo sampling technique previously discussed. It can be seen that 10% in the follower expected total profit is reduced using the contract price 0.17 m.u/kWh. However, the leader partner, would offer this price taking into consideration that the follower would accept as she/he is expected to gain in 18% (probability of acceptance) of the generated scenarios resulted from this offer. It can be noticed also that the contract price 0.19 m.u/kWh is likely to be accepted by the follower partner, with 79% probability of acceptance.

Table 6.9: Follower economic summary

	Contract price (0.17 m.u./kWh)	Contract price (0.18 m.u./kWh)	Contract price (0.19 m.u./kWh)	Standalone
Cost (x10^6 m.u.)	15.38	15.42	15.38	13.16
Sales (x10^6 m.u.)	17.83	18.13	18.33	15.90
Profit (x10^6 m.u.)	2.46	2.71	2.95	2.74

Finally, Figures (6.27 - 6.30) summarize the energy (resource r') decisions (expected in the follower case) using the different coordination contracts.

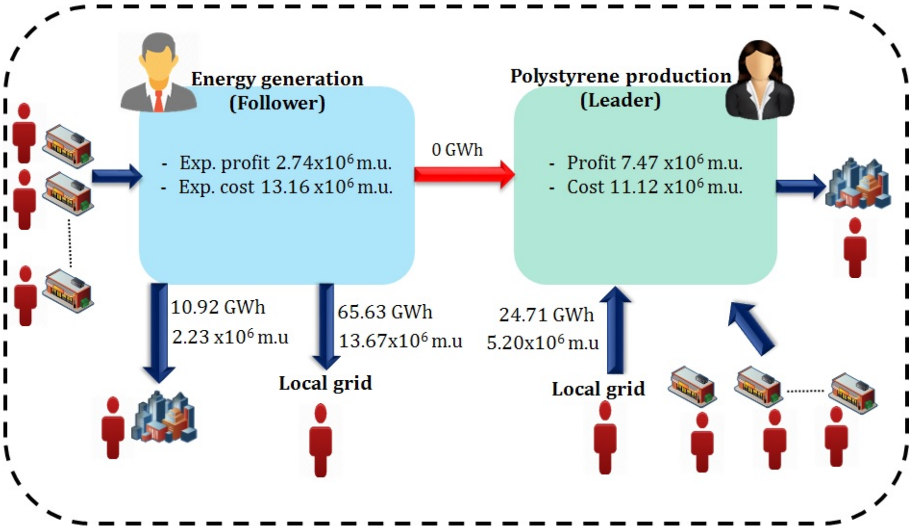


Figure 6.27: Energy expected flows (standalone)

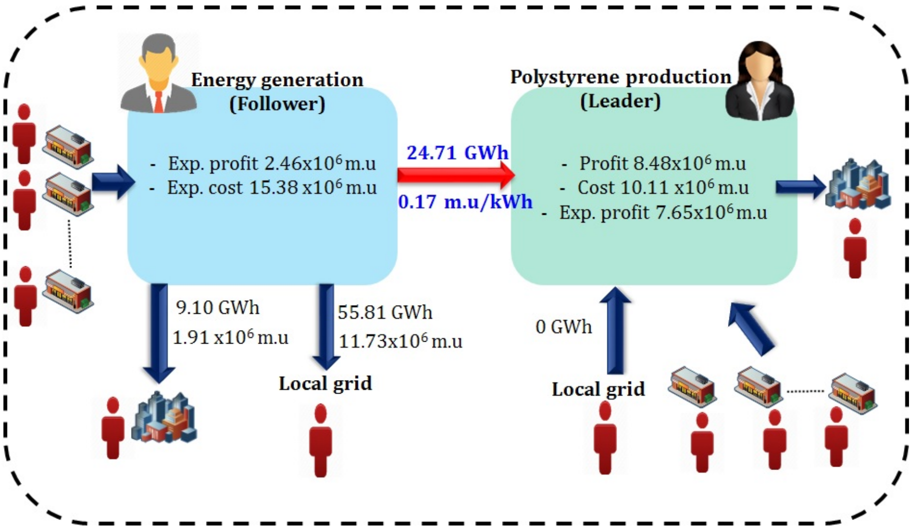


Figure 6.28: Energy expected flows (contract price: 0.17 m.u./kWh)

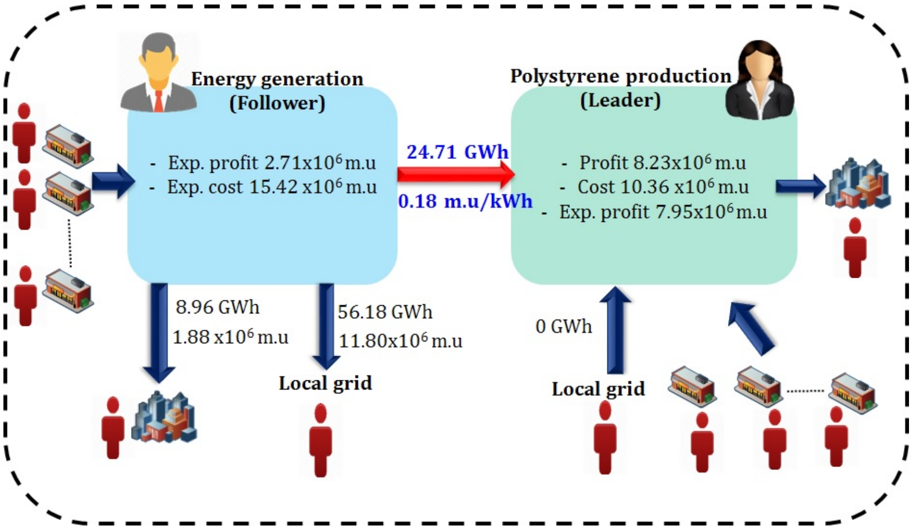


Figure 6.29: Energy expected flows (contract price: 0.18 m.u./kWh)

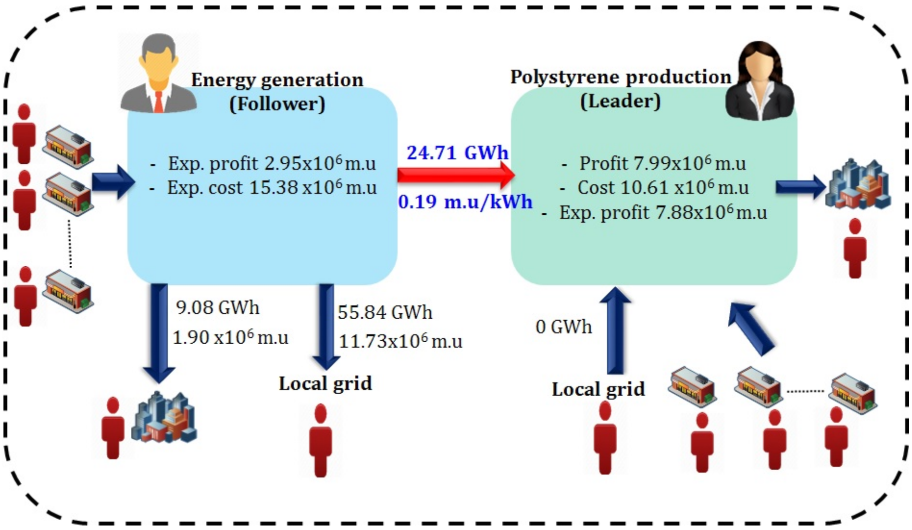


Figure 6.30: Energy expected flows (contract price: 0.19 m.u./kWh)

6.8 Final considerations

The main goal of this chapter has been to develop decision-support tools to help SC managers in making efficient decisions for multi-enterprise large-scale multi-site multi-echelon multi-product SCs from a decentralized perspective. To do so, different coordination/collaboration scenarios are analyzed based on cooperative and non-cooperative systems, and compared with the standalone system.

A Scenario-Based Dynamic Negotiation (SBDN) approach is proposed to set the best conditions for the coordination/collaboration contract between the participating enterprises of overlapping/contrasting objectives under uncertainty. Since any contract is documented between pairs of enterprises stakeholders, the rest of participants must be regarded as third parties, in which they participate in the decentralized decision-making process by their prices policies and uncertain behavior. The interaction between the negotiating enterprises (client and provider, both participate as complete SCs with their third parties "external clients and providers" is modeled through a non-cooperative non-zero-sum SBDN with non symmetric roles built on expected win-to-win principles. The client decision-maker, as the negotiation leader partner, designs a set of coordination contracts anticipating the uncertain response of the provider (as follower) resulted from the uncertain nature of the surrounding third parties. This uncertain response is modeled as probability of acceptance, which is able to capture the variations of the follower profits scenarios resulted from the Monte-Carlo sampling method. Furthermore, and unlike the reviewed literature, an assessment methodology is proposed to help SCs enterprises decision-makers to evaluate the final coordination contract agreement based on their possible risk-behavior (risk-seeking, risk-neutral, and risk averse) and cumulative probabilities.

The proposed approach is implemented through the mathematical formulations of different tactical MINLP generic and flexible models, which have been solved for a case study of a large-scale multi-enterprise multi-echelon multi-product SC with different providers and clients industrial production SCs.

The results show that using the the non-cooperative SBDN, it is possible to identify and manage high individual profits expectations likely to be accepted by all participants. The results show the importance of the transfer price on the negotiation process; for the presented case study, increasing the unit transfer price by 0.01 m.u. leads to potential increase in the cumulative probability of the follower successful profits scenarios.

Moreover, the proposed approach gives flexibility to the negotiating partners to accept/reject the coordination/collaboration, based on the fact that their individual SCs can function as standalone systems. This flexibility can be counted as added value of the proposed SBDN approach. This th leader is not given a monopolistic role in the negotiation process. Furthermore, the proposed approach identifies coordination situations that cope with the different risk behaviors of the negotiating partners decision makers.

The proposed methodologies are flexible enough to be applied to real cases when enterprises seek collaborations under different sources of uncertainty. The enterprises decision-makers are able to assess the impact of their tactical decisions and the other partners' decisions on their actions. The use of Monte-Carlo sampling method adds value to the proposed approach, as both negotiating partners can evaluate the coordination/collaboration contracts based on methodologically generated set of data and, unlike the reviewed literature, the assessment process considers the variability between the follower profits scenarios rather than the mean.

Finally, the proposed SBDN method allows the third parties to participate in the decision-making process through their price policies and uncertain behavior, thus giving them enough freedom to control their financial nodes in order to stay competitive. The uncertain nature of the third parties affects the follower response to the leader offers, and thus affects the tactical decisions of the whole system. Integrating the price policies of the competitive third parties in the tactical model formulations may lead to equilibrium situations between the each negotiating partner and the third parties of the counterpart. The characteristics of this equilibrium will be analyzed in the next chapter (Chapter 7), where the proposed SBDN method is compared with the game theory method.

6.9 Nomenclature

Indices

r	resource (raw material, product, energy, steam, cash,...)
r'	negotiation resources
sc	supply chain
t	time period

Sets

D	third parties
F	follower supply chain
L	leader supply chain
m	final customers
n	piecewise pricing zone
pl	production plants
R	resources (raw material, product, energy, steam, cash,...)
T	time period
w	warehouses/distribution centers
w'	external warehouses/distribution centers

xc	external clients
xv	external providers

Parameters

$dm_{m,sc}$	distance between final customer m and supply chain
$ds_{s,sc}$	distance between external supplier s and supply chain
$fac_{r',r,sc}$	production factor of resource r from r', leader SC
$f_{r,r',sc}$	production factor of resource r' from r, follower SC
$PE_{r',xv,sc,n}$	price elasticity of demand of resource r' purchased from external providerxv at price zone n
$PRO^{min}_{r,pl,sc,t}$	minimum production capacity of resource r in production plant pl, time t
$PRO^{max}_{r,pl,sc,t}$	maximum production capacity of resource r in production plant pl, time t
$pv^{min}_{r',xv,t,n}$	minimum price of resource r' from external provider xv, price zone n, time t
$pv^{max}_{r',xv,t,n}$	maximum price of resource r' from external provider xv, price zone n, time t
$rp_{r,sc,m}$	retail price of resource r (final product) to market m
$ST^{stock}_{r',w,sc,t}$	stock amounts of r' in warehouse w, time t
$ST^{min}_{r,w,sc,t}$	minimum storage capacity of resource r in warehouse w, time t
$ST^{max}_{r,w,sc,t}$	maximum storage capacity of resource r in warehouse w, time t
$uprdf_{r',sc}$	unit production cost of resource r', follower SC
$uprd_{r,sc}$	unit production cost of resource r
$ustr_{r,w,sc}$	unit storage cost of resource r
$ust_{r',w,sc}$	unit storage cost of resource r'
$df_{sc,w'}$	travel distance of resource r' from warehouse w', follower SC
$utrf_{r',sc}$	units transport cost of resource r', follower SC
$utrs_{r,sc}$	unit transport cost of resource r (raw material)
$utrm_{r,sc}$	unit transport cost of resource r (final product)
$VL^{min}_{r',xv,sc,t,n-1}$	minimum purchase amount of resource r' from external provider xv at price zone $n-1$, leader SC, time t
$VL^{max}_{r',xv,sc,t,n}$	maximum purchase amount of resource r' from external provider xv, price zone n, leader SC, time t
$xdem_{r,sc,m,t}$	external markets m demands of resources r, time t

Continuous variables

$C_{r',w,sc,xc,t}$	quantity flows of resource r' from warehouse w to external client xc, follower SC, time t
$COST_{sc}$	supply chain cost
CPR_{sc}	production cost
CRM_{sc}	external resources purchase cost
CST_{sc}	storage cost
CTR_{sc}	distribution cost
$EXPROF_{sc}$	leader expected profit
$FC_{r',sc,xc,t}$	quantity of resources r' sold to external client xc, follower SC, time t
$FPD_{r,r',pl',sc,t}$	production of resources r' from resources r in production plants pl, follower SC, time t

$FPRO_{r',pl,sc,t}$	production of resource r' in production plant pl, follower SC, time t
$LPRO_{r',r,pl,sc,t}$	production of resource r from resource r' in production plant pl, leader SC, time t
$MK_{r,w,sc,m,t}$	resources r flows from warehouse w to market m, time t
$p_{r',sc}$	resources r' unit transfer price
$pc_{r',xc,t}$	unit price of resources r' to external client xc, time t
$PRO_{r,pl,sc,t}$	production levels of resource r in production plant pl, time t
$PROF_{sc}$	aggregated profit
$prob_{sc}$	probability of acceptance
$pv_{r',xv,t}$	unit price of resource r' from external provider xv, time t
$pv^{min}_{r',xv,t,n}$	unit price of resource r' from external provider xv at price zone n, time t
$Q_{r',sc,t}$	resources r' flows from/to supply chain, time t
$Q_{r',w,sc,w',t}$	resource r' flows from follower warehouse w to leader warehouse w', time t
$Q_{r',w',w,sc,t}$	resource r' flows from follower warehouse w' to leader warehouse w, time t
$QL_{r',pl,t}$	resource r' demanded by production plants pl, time t
$RM_{r,s,sc,t}$	resource r (raw material) purchased from external supplier s, time t
NS_{sc}	number of successful profits scenarios
$SALE_{sc}$	economic sales
$SPROF_{sc}$	standalone profit, leader SC
$ST_{r',w,sc,t}$	storage of resources r' in warehouse w, time t
$STR_{r,w,sc,t}$	storage of resource r in warehouse w, time t
TN_{sc}	total number of generated scenarios (Monte-Carlo)
$Tprofit$	overall profit
$V_{r',xv,w,sc,t}$	resource r' flows from external provider xv to warehouses w, leader SC, time t
$VL_{r',xv,sc,t}$	resourcesr' flows from external provider xv, leader SC, time t
$VL_{r',xv,sc,t,n}$	resource r' flows from external provider xv, price zone n, leader SC, time t
$vrm_{r,s,sc,t}$	unit price of resource r (raw material) purchased from external supplier s, time t

Discrete variables

$y_{r',t,n}$	Binary variable for pricing zone n of resource r', time t

Chapter 7

Integrated Game Theory Modeling under Uncertain Competitive Environment

7.1 Introduction

The dynamic competitive nature of chemical industry SCs underscores the necessity of decision-support tools able to capture the individual objectives of all participants enterprises towards efficient multi-enterprise wide coordination (M-EWC). Current decision-support tools on decentralized SCs decision-making (Cao *et al.*, 2013; Huang *et al.*, 2013; Yue & Fengqi, 2014; Yi & Guo, 2015; Heese & Kemahlioglu-Ziya, 2016) disregard the risk associated with the presence of competitive clients and providers in an uncertain market environment, and most of the literature works do not consider the standalone case, assuming that the collaboration is a must.

In the previous chapter, a scenario-based dynamic negotiation method is proposed for the coordination between enterprises of contrasting objectives considering the uncertain reaction of the follower partner. In this chapter, the coordination contracts are obtained using Game Theory (GT), and compared with the SBDN method proposed in Chapter 6 using the same case study. The problem statement and the model formulations of the previous chapter are extended to consider the global view of the SC of interest, in which all providers and clients act as complete SCs, including the external clients and providers (third parties). The SBDN considers tha uncertainty around the follower partner SC, however the problem statement of the previous chapter is extended to consider the uncertain behavior of all participants, including the uncertain behavior of the follower partner, resulting from the uncertain nature of their third parties.

As previously described in Chapter 2, most of the literature on decentralized SCs coordination based on either cooperative or non-cooperative games focus on simple SC structures disregarding the co-existence of competitive providers/clients and their uncertain behavior. Moreover, most of the reviewed literature tends to linearize the mathematical formulations in order to simplify and to mitigate the computational efforts, which may lead to lose some practicality resulting in sub-optimal decisions. GT provides a suitable platform to solve such situations of contrasting and competitive interactions.

Current non-cooperative GT models allow to provide individual decisions based on static cases, without considering the whole SC perspective and how the other players decisions affect the whole system equilibrium. It is important to understand how the other participating enterprises may react, without giving the monopoly to one player (leader provider or client). Therefore, effective games that are able to deal with the firms contrasting objectives and their corresponding interaction including their competitive third parties are necessary in order to enhance the M-EWC and to avoid any potential disruption that may lead to withdraw important partners from the whole system.

Consequently, this chapter aims to develop an integrated GT method for the coordination of multi-enterprise Supply Chains (SCs) in a competitive uncertain environment, by suggesting the best terms for the coordination contracts between enterprises of contrasting/overlapping objectives. The proposed method considers different providers and different clients participating in a large-scale multi-echelon multi-product SC network, which gives flexibility to the game players to accept or reject the GT outcome. The contrasting objectives between the provider (production SC) and the client (manufacturing SC) are captured through a non-cooperative non-zero-sum single-leader single-follower Stackelberg game, which is built on expected win-win principles. It is important to highlight that the proposed GT method takes into account the uncertain behavior of the enterprises unfolding from the uncertain nature of their competitive third parties. The competence between each Stackelebrg game player and the counterpart third parties is expected to lead to Nash Equilibrium (NE) situation.

A novel method is proposed to represent the game theory outcome as an expected win-win Stackelberg set of "Pareto frontier", where each point corresponds to a possible coordination/collaboration contract. The Stackelberg set of Pareto frontier gives a wider set of options for the game players to negotiate later based on more information related to their SCs operational conditions and risk behaviors. The values on the Pareto frontier represent the trade-off between the enterprises payoffs. The Stackelberg payoff matrix is built under the nominal conditions, and then evaluated under different probable uncertain scenarios using a Monte-Carlo simulation. Both game players must carefully evaluate the game outcome, based on their expected payoffs and respective variances. The results show that the coordinated decisions lead to higher expected payoffs compared to the standalone cases. This leads to uncertainty reduction, and thus stressing their willingness to collaborate.

To achieve the main goal of this chapter, many objectives are to be addressed, such as:

- To integrate the Stackelberg and NE games in a single integrated GT approach.
- To bring the competitive third parties into the game as complete SCs with their price policies.
- To develop a Stackelberg set of "Pareto frontier" considering the uncertain behavior of all game players.
- To analyze the relationship between the possible coordination contracts and the "uncertainty effects reduction cost"
- To identify the resources and the economic flows through the global SC nodes that result in acceptable financial returns over a discrete planning horizon.

7.2 Problem statement

This chapter addresses the inter-organizational coordination/collaboration between different participants based on non-cooperative systems. The problem statement of Chapter 6 is extended to consider the SCs of the external provider and client as part of the global system (Figure 7.1). Two main enterprises with their complete production SCs are considered for this chapter: the provider and the main client. The main provider is supposed to sell an inner component/s to the main client and to external clients (third parties). The main client is supposed to purchase this inner component from the main provider and from external providers (third parties).

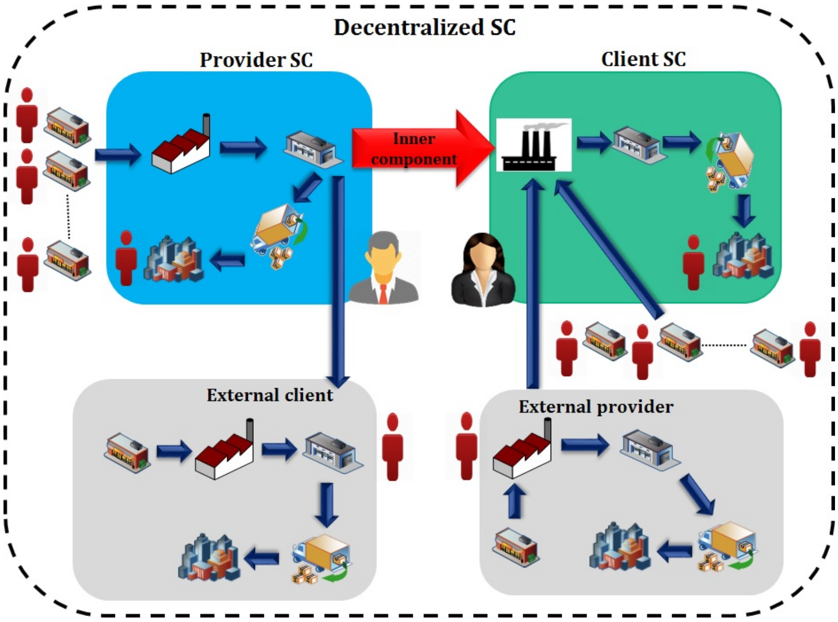


Figure 7.1: Decentralized global SC network

Under such a scenario, two main issues arise (Figure 7.2):

- Competence between providers/clients: the main provider and the external provider compete to provide resources to the main client, while the main client and the external client compete to purchase resources from the main provider.
- contrasting objectives: when the main enterprises interact the inner component "conflicting resource", where the provider enterprise seeks maximum value while the client enterprise seeks a minimum value.

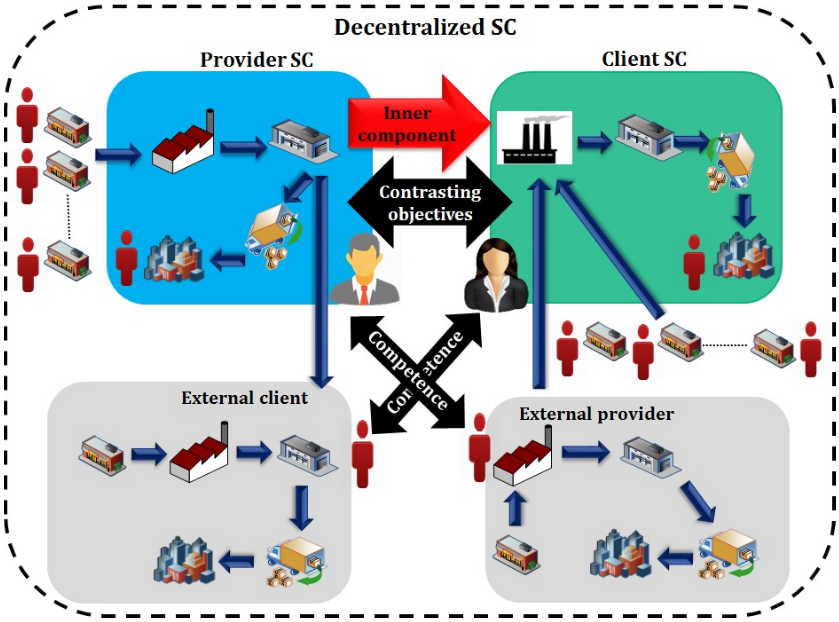


Figure 7.2: Contrasting and competitive objectives

7.3 Methodology

In order to represent the individual objectives of each enterprise, the contrasting and competitive objectives between the different actors are captured through an integrated GT (Stackelberg-NE) approach based on non-cooperative games. The Stackelberg-game is to capture the contrasting objectives, while the NE-game is to capture the competence among the players of interest.

7.3.1 Stackelberg-game

Under win-win (nominal/expected) conditions, the contrasting goals of the main provider and the main client are modeled through non-cooperative non-zero-sum single-leader single-follower Stackelberg game, with non-symmetric roles. The Stackelberg game players are the main client "as the game leader" and the main provider "as the follower". The Stackelberg game item is the inner component and the coordination/collaboration contract must include the transfer price of the game item and the inner component flows (physical/economic) between their SCs over a discrete planning horizon. The Stackelberg game reaction function is identified to be the physical flows of the inner component from the follower SC to each manufacturing plant of the leader SC. Based on the available information that each game player possesses about the other player, each one acts to optimize her/his SC individual payoff by taking into account that the other player is pursuing the same objective. The Stackelberg-game leader player makes the first move of the Stackelberg game anticipating the reaction of the follower by offering the transfer price of the game item. Consequently, the follower player reacts by optimizing its production plan to provide the offered amount of the game item (Figure 7.3). This is repeated until the Stackelberg Payoff matrix is built. Each cell of the Stackelberg Payoff matrix corresponds to a possible coordination/collaboration contract (i.e. transfer price and quantity demanded flows over time). It is worth mentioning that the Stackelberg Payoff matrix depends on the knowledge each player has previously acquainted about the other, and thus different solutions may be obtained.

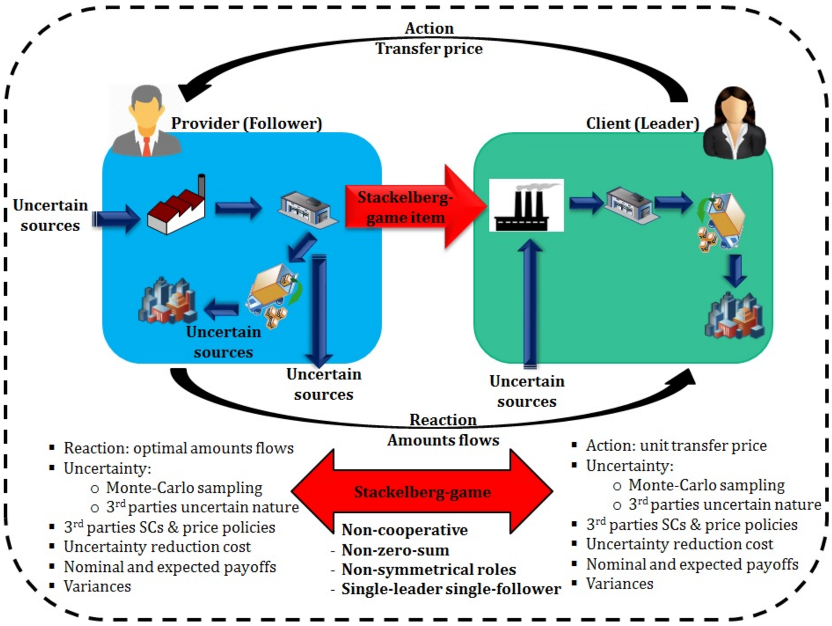


Figure 7.3: Stackelberg-game methodological framework

Next, the Stackelberg Payoff matrix is evaluated using a set of generated scenarios through a Monte-Carlo sampling method, which considers:

1. the uncertain behavior of the follower SC resulting from the uncertain prices of the resources to/from its third parties.

2. the uncertain behavior of the leader SC resulting from the uncertain prices of the resources from its third parties.

3. the uncertain behavior of both the follower and leader SCs resulting from the uncertain nature of their third parties.

The expected payoffs of the game players are obtained on the basis of generated scenarios considering the aforementioned uncertain cases. The Stackelberg game output is represented as a Stackelberg set of "Pareto frontier" that guarantees win-win outcomes (nominal/expected). Both game players must carefully evaluate the game outcome, based on their expected payoffs and respective variances.

7.3.2 Nash Equilibrium game

The Nash Equilibrium (NE) game is used as non-cooperative game when the roles of the game players are not symmetric (i.e, no one is leading the game). NE-game is used to find the best strategy for competitive situations. In this chapter, the competitive NE-game players are (see Figure 7.2):

- The main provider (Stackelberg-game follower player) and the external providers competing to sell resources to the main client (Stackelberg-game leader player).

- The main client (Stackelberg game leader player) and the external clients competing to purchase resources from the main provider (Stackelberg game follower player).

The idea of the NE-game is that each player is playing her/his best moves taking into consideration that the other player is playing also his/her best in a simultaneous way. To do so, each NE-game player must consider the best strategy of the other competitive NE-game player. The NE solution (equilibrium) is achieved when no one of the NE-game players can improve her/his payoff by changing only her/his own strategy while the other players strategies remain unchanged.

7.3.3 Integrated Stackelberg-NE Game

To integrate the Stackelberg and the NE games, each Stackelberg-game player must consider the optimal strategy of the competitive external provider/client (NE-game player) when making the Stackelberg move (transfer price/amounts). In other words, the main client must consider the optimal price strategy of the competitive external client (third party) when offering the price, and the main provider as a Stackelberg game player must consider the optimal amounts that the external provider (third party) offers to the main client. This means that the main client and the main provider play different roles: Stackelberg and NE game players.

Finally, the decisions achieved are the raw material (RM) acquisition and unit prices, the inner component flows and transfer price (game coordination/collaboration contract items), production, storage, and distribution activities and directions. The integrated methodology is explained in details in the mathematical formulations (next section).

7.4 Mathematical formulations

A generic tactical model is developed which integrates the Stackelberg-game with the NE-game in one mathematical formulation. In the next sections, the GT theoretical models are described separately (sections 7.4.1 & 7.4.2). Then, both models are integrated into a single novel GT theoretical model (section 7.4.3). Afterward, the single model will be translated into a SC tactical model multi-enterprise which is able to capture the competence and the contrasting objectives between various players.

7.4.1 Stackelberg-game theoretical model

Mathematically, a single-leader single-follower Stackelberg-game forms a bi-level model (Colson *et al.*, 2007), where the leader SC model is considered at the upper-level problem, and the follower SC model is considered at the lower-level problem. The idea of the bi-level formulation is that the leader makes her/his actions taking into consideration the optimal decisions of the follower, as both the upper-level and the lower-level problems are solved simultaneously. Eq. (7.1) summarizes the bi-level model formulation. The terms Z and z are the upper-level and lower-level objective functions, respectively. X and Y represent the upper-level and lower-level decision variables; G and H represent the upper-level inequality and equality constraints, while g and h represent the lower-level inequality and equality constraints. It can be noticed that the constraints of the upper-level problem depend on both the upper-level and lower levels decision variables (x and y). The Stackelberg-game leader player is represented by L, and the Stackelberg-game follower player is represented by F.

$$\begin{aligned} \max_{x \in X, y} Z_L(x, y) &\begin{cases} H_L(x, y) = 0 \\ G_L(x, y) \leq 0 \end{cases} \\ \textit{where}, & \\ y \in \max_{y \in Y, x} z_F(x, y) &\begin{cases} h_F(x, y) = 0 \\ g_F(x, y) \leq 0 \end{cases} \end{aligned} \tag{7.1}$$

In case the follower SC model is convex and regular, the bi-level model can be formulated by replacing the lower-level model by its Karush-Kuhn-Tucker (KKT) conditions (Bard, 1998), thus transforming it into constraints in the leader SC optimization model (upper-level problem). This manipulation results in a monolithic model that can be solved at once.

7.4.2 NE-game theoretical model

Assuming a NE-game with $i \in (1, 2...I)$ players, k_i the strategy of player i, and k_{-i} is the strategy of the rest of the competitive players (all players except i). The NE-game equilibrium is achieved when all competitive players make their strategies, simultaneously, by taking into consideration the strategies of the rest of the players. The objective function is to maximize the payoff of player i (Eq. (7.2)) taking into consideration the others players strategies.

$$O.F. \qquad \max_{k_i} f_i(k_i, k_{-i}) \tag{7.2}$$

The NE-game equilibrium strategy is achieved when none of the game players can improve her/his payoffs by changing only her/his own strategy (Eq. 7.3).

$$f_i(k_i^*, k_{-i}^*) \geq f_i(k_i, k_{-i}^*) \tag{7.3}$$

7.4.3 Integrated game model

Here, the Stackelberg-game and the NE-game theoretical models are integrated into one algorithm (Eqs. (7.4)-(7.8)), considering that the Stackelberg-game players are also NE-game players. i represents the NE-game competitive providers, and j represents the NE-game competitive clients. The Stackelberg-game Leader player L as NE-game player ($L \in J$) competes with the rest of the clients ($-j$) players. The Stackelberg-game follower player $F \in I$ as NE-game player competes with the rest of the providers ($-i$) players. So, when maximizing the payoff of the Stackelberg-game players Z_L & z_F, the strategy of the rest of the NE-game players must be considered (Eq. (7.4)).

$$\begin{aligned}
&\max_{x \in X, k \in X, y} Z_{L \in J}(x, y, k_L, k_{-j}) \begin{cases} H_L(x, y, k_L, k_{-j}) = 0 \\ G_L(x, y, k_L, k_{-j}) \leq 0 \end{cases} \\
&\qquad where, \\
&y \in \max_{y \in Y, q \in Y, x} z_{F \in I}(x, y, q_F, q_{-i}) \begin{cases} h_F(x, y, q_F, q_{-i}) = 0 \\ g_F(x, y, q_F, q_{-i}) \leq 0 \end{cases}
\end{aligned} \tag{7.4}$$

From the Stackelberg-game leader side, the NE equilibrium strategy k_L^* is achieved when the leader cannot improve her/his payoff by changing only her/his own strategy k_L (Eq. (7.5)). From the Stackelberg-game follower side as NE-game player, the NE equilibrium strategy q_F^* is achieved when the follower cannot improve her/his payoff by changing only her/his own strategy q_F (Eq. (7.6)).

$$Z_{L\in J}(x^*, y^*, k_L^*, k_{-j}^*) \geq Z_{L\in J}(x, y, k_L, k_{-j}^*) \quad (7.5)$$

$$z_{F\in I}(x^*, y^*, q_F^*, q_{-i}^*) \geq z_{F\in I}(x, y, q_F, q_{-i}^*) \quad (7.6)$$

The NE equilibrium strategy for the external clients as NE-game players $(-j)$ is achieved when no one of them can improve her/his benefits by changing only her/his own strategy (Eq. (7.7)). The NE equilibrium strategy for the external providers $(-i)$ is achieved when no one of them can improve her/his benefits by changing only her/his own strategy (Eq. (7.8)).

$$f_{-j}(k_{-j}^*, k_L^*) \geq f_{-j}(k_{-j}, k_L^*) \quad (7.7)$$

$$f_{-i}(q_{-i}^*, q_F^*) \geq f_{-i}(q_{-i}, q_F^*) \quad (7.8)$$

Then the solution of the integrated GT algorithm can be considered as the Stackelberg-NE equilibrium. In the next section, the above integrated-GT algorithm is incorporated within a practical multi-enterprise SC tactical model.

7.4.4 The tactical integrated-GT model

To represent the integrated-GT approach within a decentralized SC framework, a set of enterprises supply chains ($sc1$, $sc2...SC$) is considered with their new subsets linking each SC to its corresponding enterprise game player SC: Stackelberg-game leader and NE- game player (L), Stackelberg-game follower and NE-game player (F), external provider as NE-game player (V), and external client as NE-game player (C). The model formulation also includes the set of external suppliers s and final customers m, a set of resources r, production plants pl, warehouses/distribution centers w. The Stackelberg-game item to be negotiated is the inner component r'.

The Stackelberg and NE game strategies are represented in Figure 7.4. The Stackelberg-game leader strategy is the action which corresponds to the unit transfer price $pL_{r',sc}$ of the game item (the strategy x in Eqs. ((7.4) - (7.6)). The Stackelberg-game follower strategy is the reaction $QF_{r',sc,t}$ which corresponds to the negotiation resource amounts from the follower SC each time period t, representing y in Eqs. ((7.4) - (7.6)).

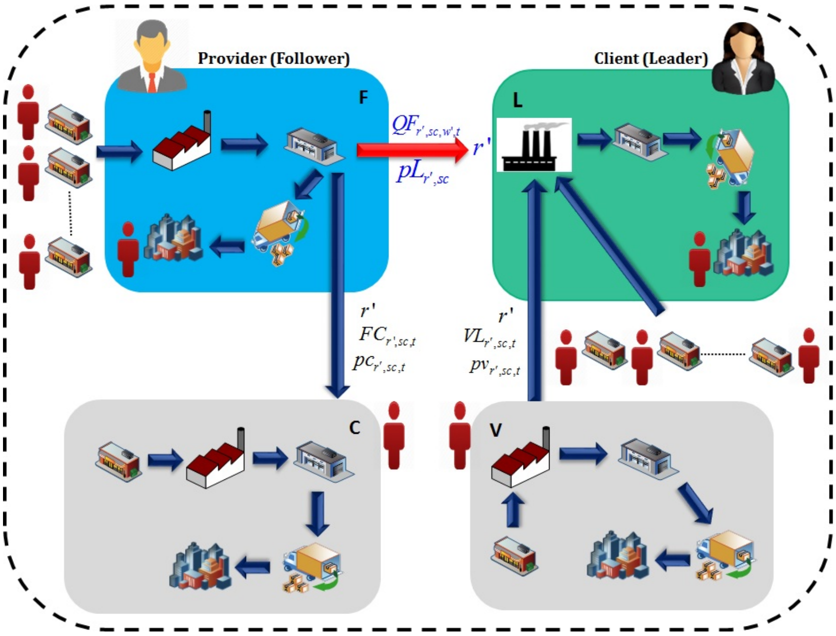


Figure 7.4: Mathematical model main items

The NE-game competitive players are represented in the mathematical formulation: competitive clients (the Stackelberg-game leader L and the external client C), and the competitive providers (Stackelebrg-game follower F and the external provider V).The NE-game players strategies are:

- The price that each client offers to the main provider: $pL_{r',sc}$ vs. $pC_{r',sc,t}$, representing the NE-game strategies k_L and k_{-j} of Eqs. ((7.4) - (7.8)).
- The amounts that each provider can sell to the main client: $QF_{r',sc,t}$ and $VL_{r',sc,t}$, representing the NE game strategies q_F and q_{-i} of Eqs. ((7.4) - (7.8)).

The Stackelberg-game reaction function $QFL_{r',sc,w',t}$ must be equal to the production levels $FPRD_{r,r',pl,sc,t}$ of the game resource item r' from resource r of the follower SC (using the production recipe represented by $f_{r,r',sc}$) minus the quantity flows to the external client (Eq. (7.9)).

$$\begin{aligned} \sum_{t\in T}\sum_{w'\in W} QFL_{r',sc,w',t} = & \sum_{\substack{r\in R \\ r\neq r'}}\sum_{pl\in PL} FPRD_{r,r',pl,sc,t}\cdot f_{r,r',sc} \\ & -\sum_{t\in T}\sum_{w'\in W} FC_{r',sc,w',t} \qquad \forall sc\in F; r'\in R; t\in T \end{aligned} \tag{7.9}$$

To avoid infeasible solutions in the leader SC model when considering the follower Stakelberbg-game strategy (reaction function), the follower Stackelberg resources flows $QFL_{r',sc,w',t}$ must be less than the maximum storage capacity $ST^{max}_{r',w',t}$ and higher than the minimum storage capacity $ST^{min}_{r',w',t}$ of the leader SC of the game resource item r' (Eq. (7.10)).

$$ST^{min}_{r',w',t} \leq QFL_{r',sc,w',t} \leq ST^{max}_{r',w',t} \qquad \forall w' \in W; sc \in F; r' \in R; t \in T \tag{7.10}$$

Eq. (7.11) illustrates the leader SC demand ($Ldem_{r',pl,t}$) of resource r', which is equal or more than the resource r' production $FPRD_{r,r',pl',sc,t}$ in the follower SC using resource r from external suppliers s multiplied by a production factor $f_{r,r',sc}$ menus the quantities sold $FC_{r',sc,sc',t}$ to external clients C each planning time period t. This production factor depends on the utilized production recipe, assuming linear correlations.

$$\begin{aligned}\sum_{pl \in PL} Ldem_{r',pl,t} \geq & \sum_{\substack{sc \in F \\ sc \in SC}} \sum_{\substack{r \in R \\ r \neq r'}} \sum_{\substack{pl' \in PL \\ pl \neq pl'}} FPRD_{r,r',pl',sc,t} \cdot f_{r,r',sc} \\ & - \sum_{\substack{sc \in F \\ sc' \in C \\ sc \neq sc'}} FC_{r',sc,sc',t} \qquad \forall r' \in R; t \in T\end{aligned} \tag{7.11}$$

The final customer demand ($xdem_{r,sc,m,t}$) of resource r may be satisfied (or not) from any participating supply chains (Eq. (7.12)), $MK_{r,w,sc,m,t}$ represents the resources flows from the warehouses w to the final customers m.

$$\sum_{w \in W} MK_{r,w,sc,m,t} \leq xdem_{r,sc,m,t} \qquad \forall sc \in SC; r \in R; m \in M; t \in T \tag{7.12}$$

Eq. (7.13) illustrates the mass balance of the game item resource r' at the warehouses of the game players SCs. $ST_{r',w,sc,t}$ corresponds to the storage levels of r' at warehouse w each time period t; $FPD_{r',pl,sc,t}$ corresponds to the follower SC production levels of r' in the production plants pl each planning time period t; $QFL_{r',w,sc,w',t}$ represents the quantity flows of r' from the warehouses w of the follower SC to the warehouses w' of the leader SC each time period t; $FC_{r',w,sc,w',t}$ represents the quantity flows of r' from the warehouses w of the follower SC to the the warehouse w' of the external client C each planning time period t.

$QL_{r',w',w,sc,t}$ corresponds to the quantity flows of r' at the warehouses w of the leader SC from the follower SC warehouses w' each time period t; $VL_{r',w',w,sc,t}$ represents the quantity of r' purchased from the external vendors SC. $LPRD_{r',r,pl,sc,t}$ is the production levels of resource r (intermediate product, final product, etc.) from r' in the leader SC production plants pl each time period t, based on the production recipe represented by $fac_{r',r,sc}$, assuming linear correlations. $FC_{r',w',w,sc}$ is the quantity flows of r' at the warehouses w of the client SC from the warehouses w' of the follower SC; $CP_{w,pl,sc,t}$ corresponds to the quantity flows from warehouses w to the production plants pl, client sc C. $VL_{r',w,w',sc}$ represents the quantity flows of r' from the warehouses w of the external provider SC to the warehouses w' of the leader SC; $VP_{w,pl,sc,t}$ corresponds to the quantity flows from warehouses w of the external provider SC to production plants pl each time period t.

$$\begin{aligned}
ST_{r',w,sc,t} + ST^{stock}_{r',w,sc,t} - ST_{r',w,sc,t-1} = \sum_{sc \in F} \sum_{pl \in PL} FPD_{r',pl,sc,t} \\
- \sum_{sc \in F} \sum_{\substack{w' \in W \\ w' \neq w}} QFL_{r',w,sc,w',t} - \sum_{sc \in F} \sum_{\substack{w' \in W \\ w' \neq w}} FC_{r',w,sc,w',t} \\
+ \sum_{sc \in L} \sum_{\substack{w' \in W \\ w' \neq w}} QL_{r',w',w,sc,t} + \sum_{sc \in L} \sum_{\substack{w' \in W \\ w' \neq w}} VL_{r',w',w,sc,t} \\
- \sum_{sc \in L} \sum_{\substack{r \in R \\ r \neq r'}} \sum_{pl \in PL} LPRD_{r',r,pl,sc,t} . fac_{r',r,sc} \\
+ \sum_{sc \in C} \sum_{\substack{w' \in W \\ w' \neq w}} FC_{r',w',w,sc} - \sum_{sc \in C} \sum_{pl \in PL} CP_{w,pl,sc,t} \\
- \sum_{sc \in V} \sum_{\substack{w' \in W \\ w' \neq w}} VL_{r',w,w',sc} + \sum_{sc \in V} \sum_{pl \in PL} VP_{w,pl,sc,t} \\
\forall r \in R; sc \in SC; w \in W; t \in T
\end{aligned} \tag{7.13}$$

Eq. (7.14) and Eq. (7.15) illustrate the production and storage minimum and maximum capacities, respectively.

$$\begin{gathered}
PRD^{min}_{r,pl,sc,t} \leq PRD_{r,pl,sc,t} \leq PRD^{max}_{r,pl,sc,t} \\
\forall r \in R; pl \in PL; sc \in SC; t \in T
\end{gathered} \tag{7.14}$$

$$ST^{min}_{r,w,sc,t} \leq ST_{r,w,sc,t} \leq ST^{max}_{r,w,sc,t} \qquad \forall r \in R; w \in W; sc \in SC; t \in T \tag{7.15}$$

Eq. (7.16) represents the NE-game strategies of the providers ($QFL_{r',sc,w',t}$ & $VL_{r',w',w,t}$). The quantity offered to the main client by the Stackelberg-game follower $QFL_{r',sc,w',t}$ must be equal or more than the total quantity needed for the leader SC manufacturing processes minus the quantity $VL_{r',w',w,t}$ offered from the competitive external provider. So, if the optimal quantity that the NE-game player V offers to the main client is known, then this optimal value can be substituted in Eq. (7.16), resulting in the NE-game equilibrium between the main providers.

$$\sum_{w' \in W} QFL_{r',sc,w',t} \geq \sum_{\substack{r \in R \\ r \neq r'}} \sum_{pl \in PL} LPRD_{r',r,pl,t} \cdot fac_{r',r,pl} - \sum_{\substack{w' \in W \\ w' \neq w}} VL_{r',w',w,t}$$

$$\forall sc \in F; r' \in R; t \in T \tag{7.16}$$

As the game is non cooperative, the objective function is to maximize the individual payoffs $PAYOFF_{sc}$ of the game players (Eq. (7.17)).

$$PAYOFF_{sc} = SALE_{sc} - COST_{sc} \tag{7.17}$$

The total SC sales $SALE_{sc}$ (Eq. (7.18)) are the sales to the final markets plus the sales to the external clients plus the sales to the leader SC. This is according to the role of the SC of interest. Here, $rp_{r,m}$ represents the retail price of the final product (r). The term ($QF_{r',sc,t} \cdot pL_{r'}$) represents the sales to the leader player SC when the SC belongs to the follower game player. The term ($VL_{r',sc,t} \cdot pV_{r',sc,t}$) represents the sales to the leader when the SC belongs to the external vendor (V).

$$SALE_{sc} = \sum_{r \in R} \sum_{m \in M} \sum_{t \in T} MK_{r,sc,m,t}, rp_{r,sc,m}$$

$$+ \sum_{sc \in F} \sum_{r' \in R} \sum_{t \in T} QF_{r',sc,t} \cdot pL_{r',sc} + \sum_{sc \in V} \sum_{r' \in R} \sum_{t \in T} VL_{r',sc,t} \cdot pV_{r',sc,t} \tag{7.18}$$

$$\forall sc \in SC$$

The SC cost (Eq. (7.19)) is the summation of the RM purchase (CRM_{sc}), production ($CPRD_{sc}$), storage (CST_{sc}), transport (CTR_{sc}), Stackelberg-game item ($QF_{r',sc,t}.pL_{r',sc}$) cost, purchase cost of resource r' from external providers ($VL_{r',sc,t}.pV_{r',sc,t}$), and purchase cost at the client SC ($FC_{r',sc,t}.pC_{r',sc,t}$), respectively. The term ($QF_{r',sc,t}.pL_{r',sc}$) and the term ($VL_{r',sc,t}.pV_{r',sc,t}$) are the inner product cost from the follower SC and from the external provider in case the SC of interest belongs to the leader L each time planning period t. The term ($FC_{r',sc,t}.pC_{r',sc,t}$) is the purchase cost of r' from the follower SC in case the SC of interest corresponds to the external client C. Here can be understood the contrasting objectives between the Stackelberg-game players, as the same term ($QF_{r',sc,t}.pL_{r',sc}$) is considered as a sale when the SC belongs to the follower F (Eq. 7.18), while it is considered as a cost when the SC belongs to the leader L (Eq. 7.19).

$$\begin{aligned} COST_{sc} = CRM_{sc} + CPRD_{sc} + CST_{sc} + CTR_{sc} \\ + \sum_{sc\in L}\sum_{r'\in R}\sum_{t\in T} QF_{r',sc,t}.pL_{r',sc} + \sum_{sc\in L}\sum_{r'\in R}\sum_{t\in T} VL_{r',sc,t}.pV_{r',sc,t} \\ + \sum_{sc\in C}\sum_{r'\in R}\sum_{t\in T} FC_{r',sc,t}.pC_{r',sc,t} \qquad \forall sc \in SC \end{aligned} \tag{7.19}$$

The RM purchase CRM_{sc} cost (Eq. (7.20)) from the external suppliers s is the RM purchased quantity ($RM_{r,s,sc,t}$) multiplied by the RM unit price ($vrm_{r,s,sc,t}$), which is computed following the piecewise pricing model proposed in Chapter 5, where different unit prices are offered by the external suppliers s depending on the quantity demanded, based on the elasticity demand theory.

$$CRM_{sc} = \sum_{r\in R}\sum_{s\in S}\sum_{t\in T} RM_{r,s,sc,t}.vrm_{r,s,sc,t} \qquad \forall sc \in SC \tag{7.20}$$

The production cost CPR_{sc} is computed on the basis of the unit production cost ($uprd_{r,sc}$) in each production plant pl as in Eq. (7.21). $PRD_{r,pl,sc,t}$ corresponds to the production levels of resource r in production plants pl each planing time period t.

$$CPRD_{sc} = \sum_{t\in T}\sum_{pl\in PL}\sum_{r\in R} PRD_{r,pl,sc,t}.uprd_{r,pl,sc} \qquad \forall sc \in SC \tag{7.21}$$

The SC storage cost CST_{sc} is computed on the basis of the unit storage cost ($ust_{r,w,sc}$) of resource r in each warehouse w each planning time period t (Eq. (7.22)).

$$CST_{sc} = \sum_{t\in T}\sum_{w\in W}\sum_{r\in R} ST_{r,w,sc,t}.ust_{r,w,sc} \qquad \forall sc \in SC \tag{7.22}$$

The SC transport cost (CTR_{sc}) is calculated in function of the travel distance $dis_{r,sc}$ of resource r and the unit transport cost $utr_{r,sc}$ (Eq. (7.23)).

$$CTR_{sc} = \sum_{t\in T}\sum_{r\in R} Q_{r,sc,t}.dis_{r,sc}.utr_{r,sc} \qquad \forall sc \in SC \tag{7.23}$$

It is assumed that the optimal strategy of the NE-game players lie in a range of different possible values, in which any value behind these ranges results in reducing the payoff of any of their SCs. For example, it is assumed that the NE-game strategy $pC_{r',sc,t}$ follow the piecewise price model with n optimal cases (Eqs.(7.24) - (7.28)). Different optimal sets of prices are offered by the NE-game player (external client SC C) to the follower player according to the quantity purchased each time period t, $FC_{r',sc,t,n}$ corresponds to the quantity purchased from the follower at unit price $pC_{r',sc,t,n}$ (NE-game strategy) at each pricing zone n each time period t. The binary variable $x_{r',t,n}$ is used to allocate each purchase quantity $FC_{r',sc,t}$ to its corresponding unit price $pC_{r',sc,t}$.

$$\begin{aligned} x_{r',t,n}.FC^{min}_{r',sc,t,n-1} \leq FC_{r',sc,t,n} \leq x_{r',t,n}.FC^{max}_{r',sc,t,n} \\ \forall r' \in R; sc \in C; t \in T; n \in N \end{aligned} \tag{7.24}$$

$$\begin{aligned} x_{r',t,n}.pC^{min}_{r',sc,t,n} \leq pC_{r',sc,t,n} \leq x_{r',t,n}.pC^{max}_{r',sc,t,n-1} \\ \forall r' \in R; sc \in C; t \in T; n \in N \end{aligned} \tag{7.25}$$

$$pC_{r',sc,t} = \sum_{n\in N} pC_{r',sc,t,n} \qquad \forall r' \in R; sc \in C; t \in T \tag{7.26}$$

$$FC_{r',sc,t} = \sum_{n\in N} FC_{r',sc,t,n} \qquad \forall r' \in R; sc \in C; t \in T \tag{7.27}$$

$$\sum_{n\in N} x_{r',sc,t,n} \leq 1 \qquad \forall r' \in R; sc \in C; t \in T \tag{7.28}$$

The NE-game player (external provider V) optimal strategy $VL_{r',sc,t}$ is integrated in the same way.

Uncertainty management

The expected payoff ($ExPAYOFF_{sc}$) (Eq. (7.29)) of the SC is evaluated using NS generated probable uncertain scenarios around a specific mean (μ) and standard deviation (σ). Monte-Carlo sampling method is used for this regard. The expected payoff then is calculated as the mean of the resulted set of of payoffs scenarios $PAYOFF_{sc,ns}$.

$$ExPAYOFF_{sc} = \frac{\sum_{ns \in NS} PAYOFF_{sc,ns}}{NS} \qquad \forall sc \in SC \tag{7.29}$$

A simplified way to calculate the probability of acceptance $prob_{sc}$ is adopted from Chapter 5 based on the follower payoffs successful scenarios; SN_{sc} and TN_{sc} correspond to the successful and total number of the follower SC payoffs scenarios (Monte-Carlo sampling) (Eq. (7.30)).

$$prob_{sc} = \frac{SN_{sc}}{TN_{sc}} \qquad \forall sc \in F \tag{7.30}$$

As a result of the integrated GT mathematical formulation, MINLP non-convex models are obtained. In this case, solving the Stackelberg-game leader and folower MINLP models as a bi-level model using the traditional Karush-Kuhn-Tucker (KKT) conditions method (see Section 3.4 in Chapter 3) is impossible (Bard, 1998; Colson *et al.*, 2007), as the follower MINLP non-convex model cannot be reduced into constraints, unless it is simplified to an LP model formulation. Accordingly, and in order not to lose practicality and to avoid sub-optimal decisions, an alternative method is proposed by building the Stackelberg-payoff matrix.

The developed integrated-GT tactical model formulation is generic and flexible enough to be applied when different clients and providers participate in a decentralized large-scale SC. It is able to capture the contrasting and competitive objectives in one single comprehensive approach. The mathematical model is able to cope with the different roles the same game player may act. Each SC enterprise stakeholder can act as a provider for other clients' SC/s, and as a client for other providers' SC/s. The flexibility of the generic model and its ability to contain all possible SCs (centralized/decentralized, standalone) including the third parties SCs adds to the PSE and OR researches a new comprehensive approach able to solve complex decentralized decision-making structures. Furthermore, evaluating the expected payoffs of the participating SCs enterprises stakeholders helps in reducing the uncertainty effects that each game player may face due to the uncertain market environment.

7.5 Case study

To illustrate the practicality of the proposed integrated GT approach, the resulting MINLP tactical models are implemented and solved for the same case study of Chapter 6 in order to compare the obtained results.

The Stackelberg-game players are the polystyrene production SC enterprise decision-maker (as leader), and the energy generation SC (as follower), participating as complete SCs (Figure 7.5).

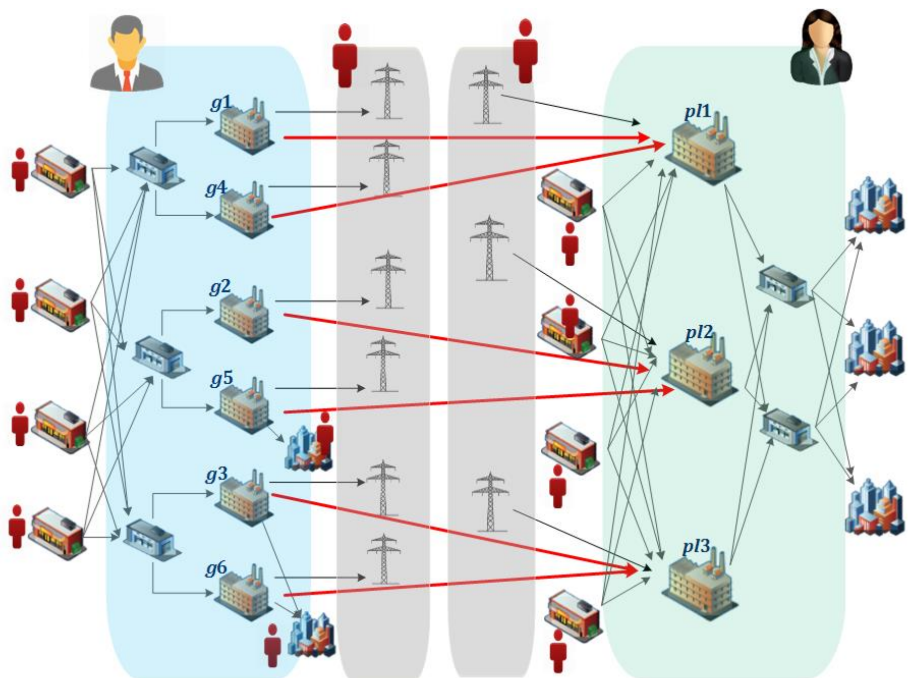


Figure 7.5: Decentralized SC game players

The Stackelberg-game follower player is supposed to sell energy to the Stackelberg-game leader player SC and also to the local grid as external client. The polystyrene manufacturing SC is supposed to purchase energy from the energy generation SC and from the local grid as external provider. The leader action is the internal energy unit transfer price. The Stackelberg-game leader offers between 0.14 m.u./kWh and 0.22 m.u./kWh. The reaction function of the Stackelberg game is the internal energy amounts that the follower provides to each production site of the leader SC along a planning horizon of 6 time periods.

The electricity local grid plays different roles in the decentralized decision-making process as NE-game players: external provider competing with the

Stackelberg-game follower, and external client competing with the Stackleberg-game leader .It is assumed, for comparison issues with the SBDN, that the electricity grid participates as simple two-echelons SC (seller-buyer SC). The Spanish local grid is considered for this work with current (selling/purchasing) nominal prices as shown in Table 6.1 of the previous chapter. To obtain the expected payoffs of the game players, 500 scenarios are generated for each of the energy price policies of the supporting third parties, using Monte-Carlo sampling method, assuming normal distribution with equal probabilities: standard deviation (σ) = 0.03; the mean (μ) for the energy prices of the third parties around the follower SC is equal to the current energy prices as in Table 6.1. For the leader SC, the mean (μ) is the external provider energy prices according to the quantity demanded as in Table 7.1.

Table 7.1: The mean (μ) of the local grid (external provider) energy prices

	μ (m.u./kWh)
Local grid energy price to polystyrene SC (demand<2GWh)	0.20
Local grid energy price to polystyrene SC (2GWh<demand<4GWh)	0.19
Local grid energy price to polystyrene SC (4GWh<demand<8GWh)	0.18

To be more practical, all RM suppliers (third parties) participate in the decentralized decision-making by their pricing policies following the piecewise pricing model of Chapter 5.

Assumptions

- The optimal strategies of the NE-game players (local grid as external provider and external client) are known within a range (optimal zones). For example, the best strategy for the local grid as competitive provider lies between 2GWh to 8GWh which are assigned to energy prices (0.20 m.u/kWh to 0.22 m.u./kWh). The best strategy of the local grid as a NE-game competitive client lies within the price range (0.19-0.21 m.u./kWh) as in Table 6.1.
- The transport and the storage costs of the RM from the external suppliers are charged by the RM buyers (energy generation enterprise/polystyrene manufacturing enterprise).
- The energy sold/purchased can not be stored.

7.6 Results and discussion

The resulting non-cooperative non-zero-sum integrated GT model has been solved for the above-mentioned case study, and the Stackelberg-payoff matrix is built under the nominal conditions (energy prices around the decentralized SC as in Table 6.1, considering the NE-game competitive players optimal strategies. Then the nominal Stackelberg-payoff matrix is evaluated under different uncertain disruptions:

1. The follower uncertain conditions resulted from the uncertain nature of its third parties. 500 probable scenarios are generated for the energy prices around the follower SC (σ = 0.03, μ = energy prices as in Table 6.1.

2. The leader uncertain conditions resulted from the uncertain nature of its 3rd party. 500 probable scenarios are generated for the energy prices of its third parties (σ =0.03, μ = energy prices as in Table 7.1).

3. The uncertain external conditions of the leader and follower resulting from both of the aforementioned cases above.

The case study is modeled using the General Algebraic Modeling System GAMS 24.2.3 on a Windows 7 computer with Intel Core^{TM} i7-2600 CPU 3.40GHz processor with 16.0 GB of RAM. The resulting MINLP tactical models have been solved for 6 time periods; 1000 working hours each, using Global mixed-integer quadratic optimizer "GloMIQO" (Misener & Floudas, 2013). The R-project program 3.2.1 is used for statistical computing. The tactical decisions achieved are the RM acquisition, game items flows and unit transfer prices, production, storage, and distribution levels. Table 7.2 summarizes the model statistics of each game player model. The CPU times when considering uncertainty is multiplied by the number of the generated scenarios.

Table 7.2: Models statistics

Game player	Model	Single equations	Single variables	Discrete variables	CPU (sec) each action
Leader	MINLP	964	1653	126	7.95
Follower	MINLP	1202	1289	180	3.85

7.6.1 Coordination under nominal conditions

The above-mentioned case study is solved at the nominal conditions (at the energy prices around the decentralized SC, as in Table 6.1). The nominal payoffs of the Stackelberg-game players are obtained for each leader action (energy unit transfer price) and follower reaction (internal energy flows) (Table 7.3). The marked payoffs values in the table are obtained based on the proposed leader transfer price and the follower optimal amounts. When the leader offers transfer prices from 0.14 m.u./kWh to 0.16 m.u./kWh, the follower responds with 0 GWh energy amounts, returning to its SC standalone case (payoff= 2.44 x10^6 m.u.). But, when the leader increases the transfer price to 0.17 m.u./kWh, the best for the follower is to provide 6 GWh distributed among the leader manufacturing plants along 6 time periods. When the leader offers 0.18-0.19 m.u./kWh, the best for the follower is to provide 23.10 GWh. When the leader offers up to 0.22 m.u./kWh, the follower is ready to sell all the energy amounts (24.71 GWh) needed for the leader SC production.

The Stackelberg-payoff matrix is represented in Figure 7.6. The leader and the follower nominal standalone payoffs are obtained to be used as benchmarks for bounding the winning zone. It is noticed that at energy prices from to 0.14-0.17 m.u./kWh, the leader is winning while the follower is losing (contrasting objectives) until reaching to the prices 0.17-0.20 m.u./kWh where the win-win zone lies. The coordination/collaboration among their SCs is viable in the win-win zone as their willingness to collaborate increases.

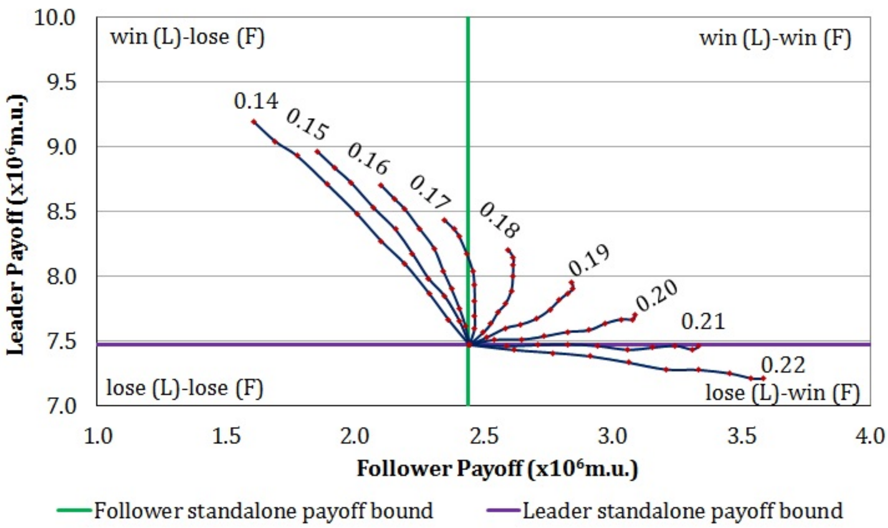


Figure 7.6: Leader payoffs vs. follower payoffs

Table 7.3: Stackelberg Payoff matrix (nominal conditions)

	Leader (L) payoff vs. follower (F) payoff (x10^6 m.u.)																	
Leader action (m.u/kWh) →	0.14		0.15		0.16		0.17		0.18		0.19		0.20		0.21		0.22	
Follower reaction (GWh)↓	F	L	F	L	F	L	F	L	F	L	F	L	F	L	F	L	F	L
0	2.44	7.47	2.44	7.47	2.44	7.47	2.44	7.47	2.44	7.47	2.44	7.47	2.44	7.47	2.44	7.47	2.44	7.47
3.00	2.36	7.66	2.41	7.66	2.43	7.61	2.46	7.59	2.50	7.57	2.51	7.53	2.54	7.51	2.59	7.46	2.62	7.43
6.00	2.29	7.87	2.35	7.85	2.41	7.75	2.47	7.69	2.53	7.63	2.59	7.60	2.65	7.51	2.71	7.47	2.77	7.41
9.00	2.20	8.09	2.29	7.98	2.37	7.90	2.46	7.81	2.56	7.72	2.64	7.63	2.74	7.54	2.83	7.47	2.91	7.38
12.00	2.10	8.27	2.22	8.17	2.34	8.04	2.46	7.94	2.58	7.79	2.70	7.67	2.82	7.57	2.94	7.46	3.06	7.33
15.00	2.01	8.48	2.16	8.36	2.31	8.21	2.46	8.04	2.61	7.89	2.76	7.74	2.91	7.58	3.06	7.43	3.21	7.28
18.00	1.89	8.71	2.07	8.53	2.25	8.36	2.43	8.18	2.61	8.00	2.79	7.82	2.97	7.64	3.15	7.45	3.33	7.28
21.00	1.77	8.93	1.98	8.72	2.19	8.52	2.40	8.31	2.61	8.09	2.82	7.87	3.03	7.67	3.24	7.46	3.45	7.25
23.10	1.69	9.04	1.92	8.83	2.15	8.60	2.38	8.36	2.62	8.14	2.85	7.91	3.08	7.67	3.31	7.44	3.54	7.21
24.71	1.61	9.19	1.85	8.96	2.10	8.70	2.35	8.43	2.60	8.21	2.84	7.95	3.09	7.70	3.34	7.46	3.58	7.21

Since the transfer prices (0.17-0.20 m.u./kWh) with the follower corresponding amounts lead to a win-win coordination/collaboration, more transfer price possibilities are examined within the same range (0.175-0.205 m.u./kWh) in order to reach a decent coordination/collaboration contract (Figure 7.7). Different Stackelberg set of Pareto solutions can be established (the dark lines/points) as in the figure, where each point on the graph corresponds to an optimal contract of coordination, but they do not guarantee the equilibrium.

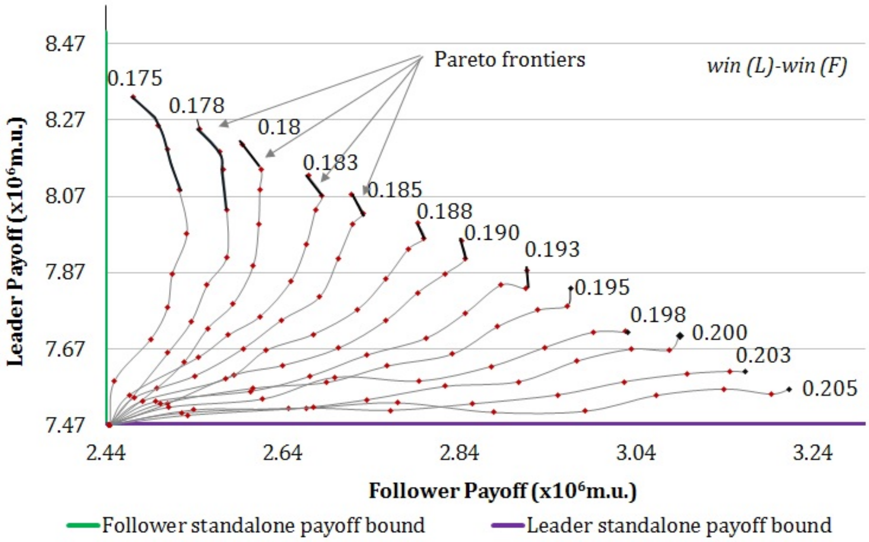


Figure 7.7: Stackelberg set of Pareto solutions (nominal conditions)

As shown in Figure 7.8, a Pareto trade-off between the players benefits can be established if the leader offers are between 0.175 and 0.205 m.u./kWh. Accordingly, the Stackelberg equilibrium is represented as a set of Pareto frontier, the so called Stackelberg set of "Pareto frontier", so to give the game players a wide range of options to be negotiated, simultaneously, based on more data available, risk behavior, and preferences. Analyzing the extreme points on the Pareto frontier, the highest leader payoff is 8.33x10^6 m.u. (at price 0.175 m.u./kWh) is 11.5 % higher than its SC standalone payoff. This value results in the lowest follower Payoff (2.47x10^6 m.u.); 1.1 % higher than its nominal standalone payoff. On the other side, the highest follower payoff is 3.21x10^6 m.u. (at price 0.205 m.u./kWh and energy amount 24.71 GWh); 31.4 % higher than its standalone payoff. This point corresponds to the lowest leader payoff (7.56x10^6 m.u.); 1.2 % higher than its standalone payoff. In any of the solution points between those extreme solutions on the Stackelberg set of "Pareto frontier", the follower shall be able to offer all the required energy to the leader (24.71 GWh) with a significant profit potential with respect to the standalone case, and the leader would also obtain benefits from this deal. Other equilibrium points can be found in this game, but they do not take the maximum profit of this win-win potential.

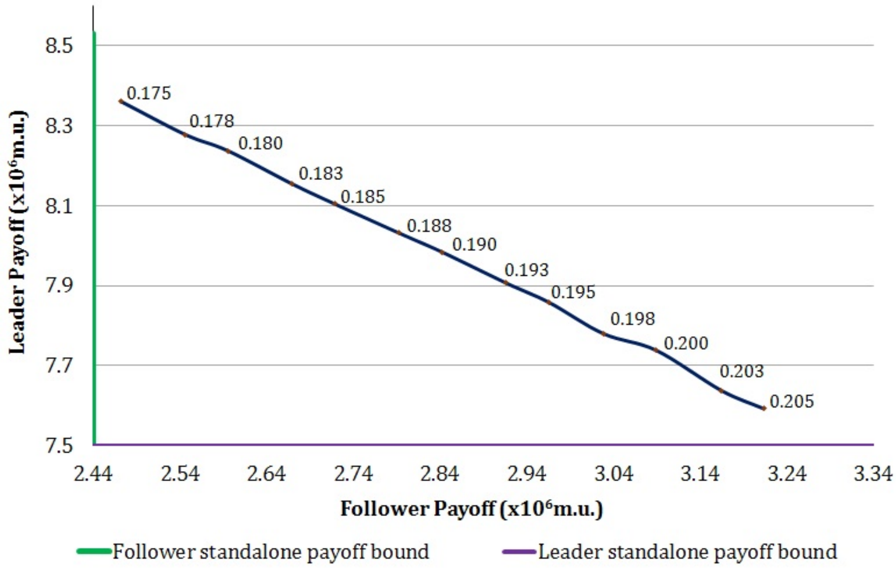
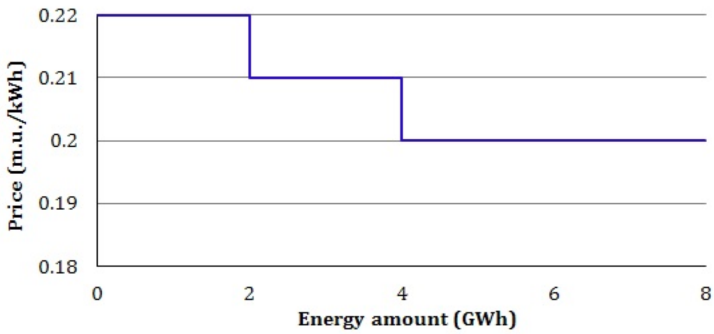
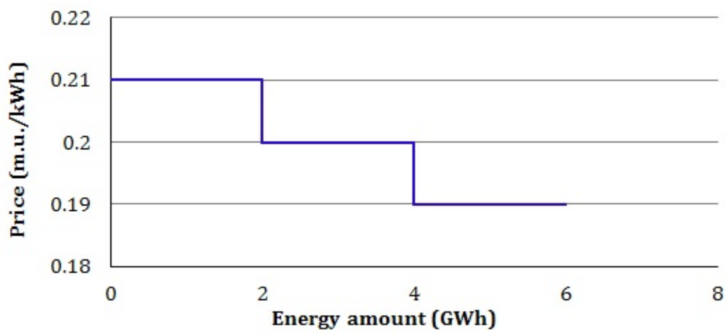


Figure 7.8: Stackelberg set of Pareto frontier (nominal conditions)

It is worth mentioning that each point on Figures (7.6 & 7.7) leads to a NE solution but does not guarantee a Stackelberg equilibrium, However, just the points on the "Pareto frontier" (Figure 7.8) lead to Stackelberg and NE equilibrium. The NE-game competitive providers are competing for the total demand of 24.71 GWh. However, the equilibrium is that the follower sells the entire amount to the leader SC, while the local grid (as NE-game provider) sells zero amount, as its optimal price range is still high (Figure 7.9(a)). So that if the local grid tries to change its strategy through its restricted optimal price policy, still the leader will buy all the energy amounts form the follower, as the follower does not restrict any amounts limits to specific prices. The local grid (as NE-game player client) has its optimal price strategy restricted to specific energy amounts (Figure 7.9(b)). So, the equilibrium is that the follower sells the 24.71 GWh without price restrictions to the leader. So, no one of the NE-game provides nor clients can improve its benefits by just moving through its optimal strategy, as mentioned before, each optimal strategy is considered in the model formulations as one package.



(a) NE-game player (external provider)

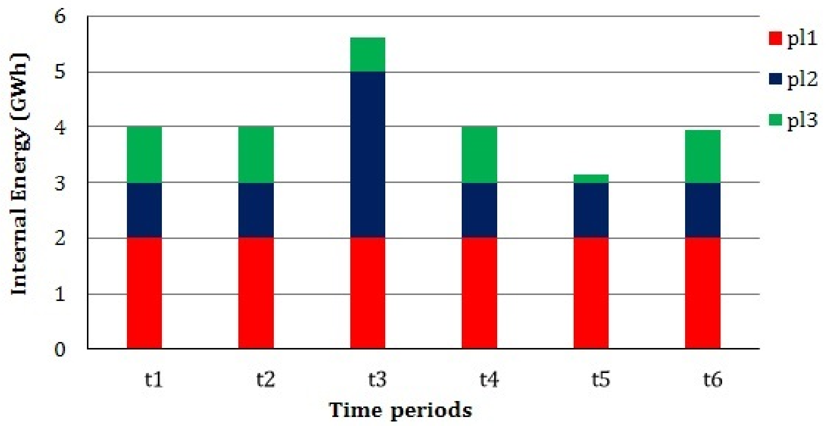


(b) NE-game player (external client)

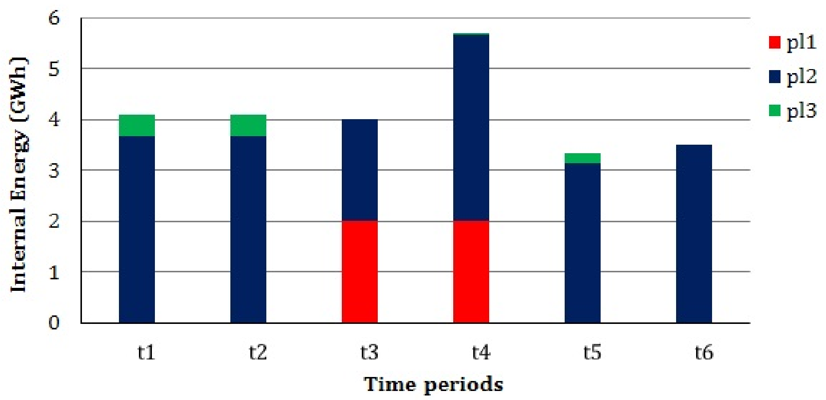
Figure 7.9: Local grid optimal strategies

7.6.2 Tactical decisions: Leader SC

The tactical decisions, associated to the trade-off between the benefits of the different players, are affected by the Stackelberg-NE equilibrium. For example, Figure 7.10 shows the internal energy flows from the follower SC to the leader SC polystyrene manufacturing plants at a possible coordination contract: 24.71GWh at 0.185 m.u./kWh (Figure 7.10(a)), namely the 5$^{\text{th}}$ point on the "Pareto frontier" from the left of Figure 7.8, comparing with the standalone case (Figure 7.10(b)). It is noticed that in the standalone case, the leaders decision should be to shutdown polystyrene plant $pl3$ because of the local grid energy market prices, which are higher at low demand levels. However, a proper coordination contract would enable to maintain the polystyrene plant $pl3$ working, so both leader and follower may get higher benefits. Furthermore, the coordination contract leads to function the polystyrene manufacturing plant $pl1$ all time periods at its manufacturing capacity to produce product B, in which the energy will be provided from the energy generation plant $g4$. Functioning the polystyrene manufacturing plant $pl1$ leads to higher benefits as it is the closest to the $rm4$ supplier (see Table Appendix B.10) which dominates the RM purchase levels for producing polystyrene product B.



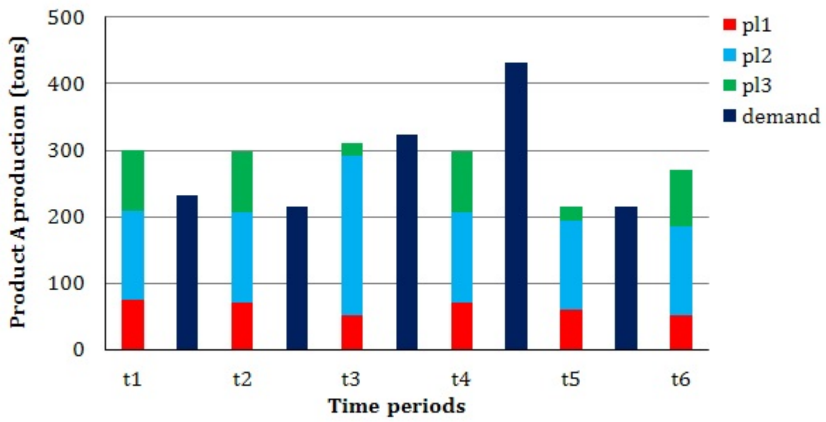
(a) Contract price: 0.185 m.u./kWh



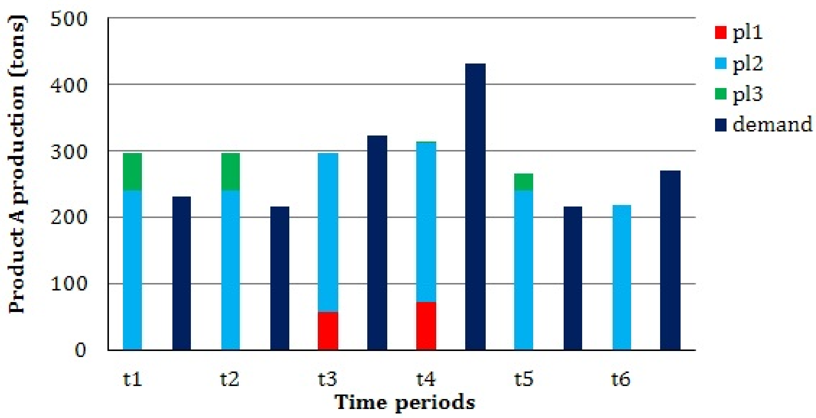
(b) Standalone

Figure 7.10: Internal energy flows to polystyrene manufacturing plants

It is worth noticing from Figure 7.11 that in order to produce product A, the polystyrene production plant $pl2$ dominates the production levels: 54.1 % of the total product A amounts under the coordination contract (0.185 m.u./kWh for 24.71 GWh) (Figure 7.11(a)), and 83.9 % under the standalone case (Figure 7.11(b)). Unlike the standalone case, the collaboration between the follower and the leader players would maintain all the polystyrene manufacturing plants working at all time periods to produce product A following the internal energy provided from the follower (Figure 7.10(a)). The dominance of the polystyrene production plant $pl2$ for producing product A can be explained by the short distance between $pl2$ and the RM supplier $sup2$ (see Table Appendix B.10), as the RM $rm2$ dominates the RM purchase levels for producing product A (see Figure 7.13). Furthermore, polystyrene manufacturing plant $pl2$ has the highest production capacity among the other plants.



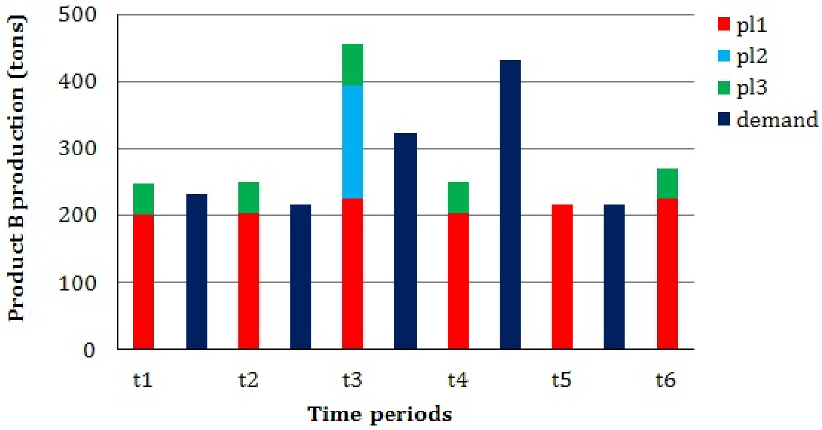
(a) Contract price: 0.185 m.u./kWh



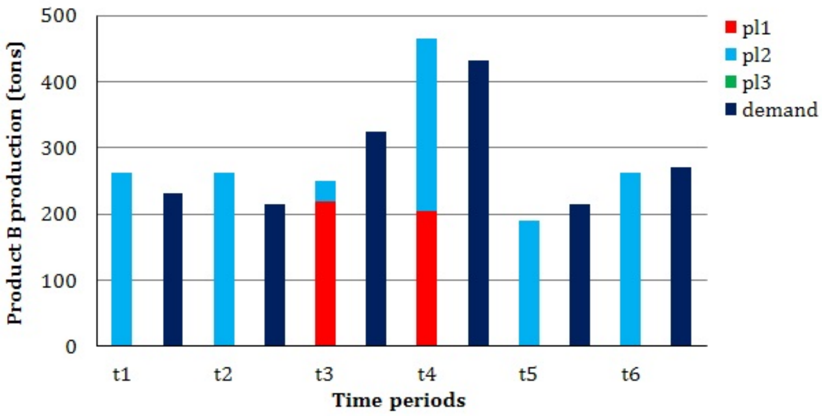
(b) Standalone

Figure 7.11: Product A production levels

Instead, to produce polystyrene product B (Figure 7.12), the coordination would lead to the dominance of production plant $pl1$ (75.4% of the total product B), as it is the closest to the $rm4$ supplier as explained before. However, at the standalone case, the production plant $pl2$ dominates again producing product B (75 % of the total production of product B) due to the local grid energy (as external provider) higher prices at low demand levels (see Figure 7.9(a)). So, the leader decision is to purchase higher amounts of energy for the production plant $pl2$ to gain lower prices and functioning it up to its production capacity to produce both products A and B.



(a) Contract price: 0.185 m.u./kWh

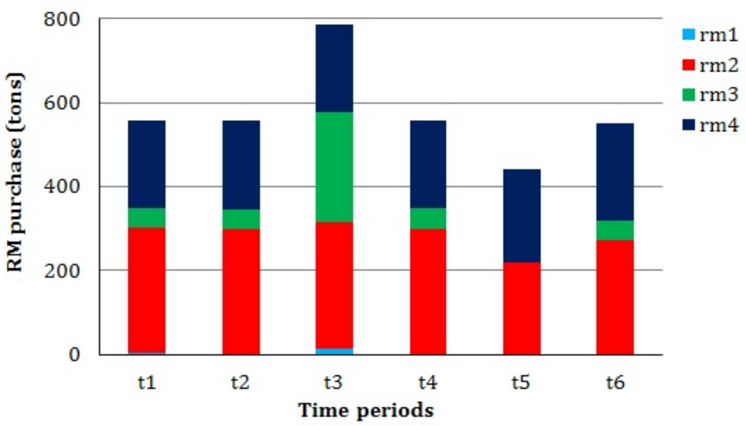


(b) Standalone

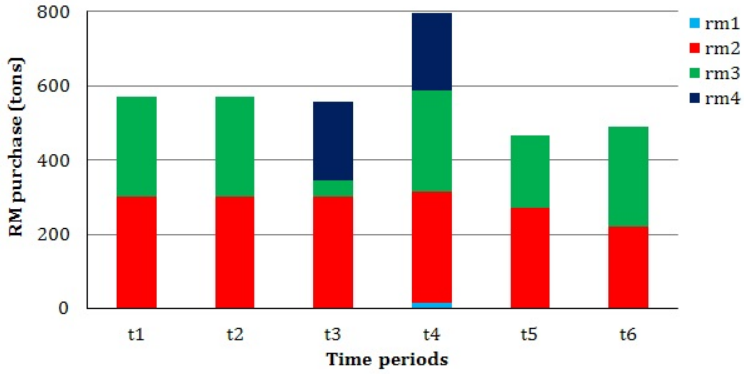
Figure 7.12: Product B production levels

Figure 7.13 shows the RM purchase levels at the possible coordination contract, 0.185 m.u./kWh : 24.71 GWh, comparing with the standalone case. It is noticed that $rm2$ dominates the RM purchase levels; 49 % (1690.91 tons) of the total RM purchase levels to produce polystyrene product A. The dominance of $rm2$ is due to its lower price and higher capacity comparing with $rm1$ (see Table Appendix B.7). Under the coordination contract, the $rm2$ purchase levels are the highest (785.83 tons, namely, 22.8 %) at time period $t3$ (Figure 7.13(a)), as the production levels of product A are the highest at the same time period (see Figure 7.11(a)). However, under the standalone case, the $rm2$ purchase levels are the highest (796.36 tons, namely 23.10 %) at time period $t4$ (Figure 7.13(b)) so to satisfy the high polystyrene production levels at the same time period (Figure 7.11(b)).

For producing product B, $rm4$ dominates the RM purchase levels (1298.39 tons, or else 37.6 %) (Figure 7.12(a)), comparing with the standalone case, so to satisfy the production levels of $pl1$, which is the closest to $rm4$ supplier. Furthermore, the decision is to purchase $rm4$ up to its supplying capacity (240 tons), so to get the highest price discount. At the standalone case, $rm3$ dominates the RM purchase levels (1320.11 tons, namely 38.3 %) for producing polystyrene product B (Figure 7.13(b)) as its supplier $sup3$ is the closest to the polystyrene production plant $pl2$ (see Table Appendix B.10) which dominates the production levels of product B (Figure 7.12(b)). Moreover, at the standalone case, the polystyrene production plant $pl2$ is working up to its production capacity, stressing the necessity to buy higher amount of RM with higher supplying capacity to get the highest possible discount, as briefely described in Chapter 5. So, the $rm3$ is the best option here. The excess of the production will be stored for later distribution.



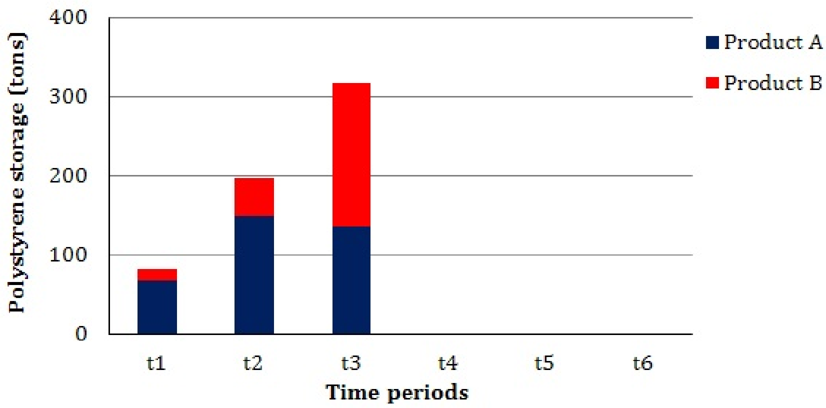
(a) Contract price: 0.185 m.u./kWh



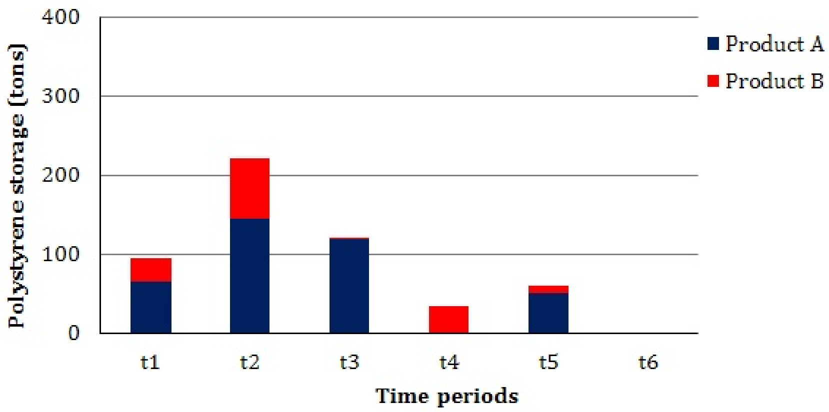
(b) Standalone

Figure 7.13: Leader RM purchase levels

Consequently, the storage decisions (Figure 7.14) are affected by the manufacturing levels resulted from the coordination. The coordination contract (24.71 GWh at 0.185 m.u./kWh) would result in 8.8 % decrease in the total storage of product A (350.05 tons) (Figure 7.14(a)), as the production activities are distributed among the 3 polystyrene manufacturing plants to produce product A. The storage levels of product B is increased by 246.30 tons; 64.8 % higher than the standalone case, and this is due to the high production levels of product B at time period $t3$ (Figure 7.12(a)) following the high internal energy provided by the follower at this time period (Figure 7.10(a)). The excess of the polystyrene production will be stored for later distribution.



(a) Contract price: 0.185 m.u./kWh



(b) Standalone

Figure 7.14: Leader SC storage levels

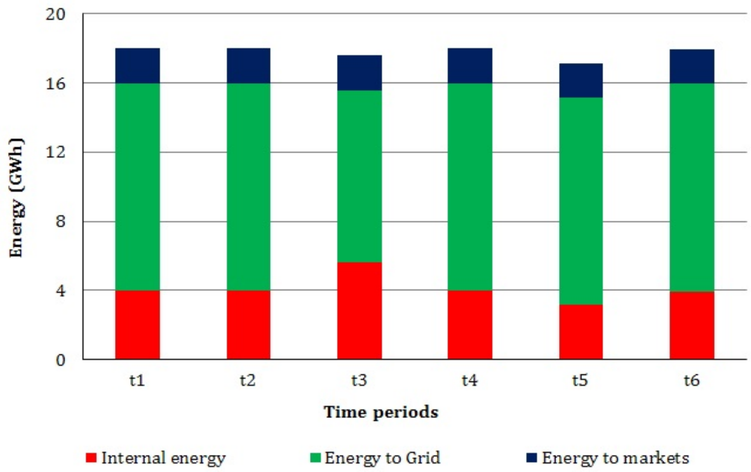
Table 7.4 summarizes the economic decisions of the leader. The total economic sales are the same (18.59x10^{6}m.u.) as the decision is to fulfill the final polystyrene markets demands. The coordination based on 24.71 GWh internal energy at price 0.185 m.u./kWh would improve the total cost of the leader SC with 5.7 % (with 0.60x10^{6}m.u. savings), in comparison with the standalone case. This leads to 7.5 % gains in 6 time periods, in comparison with the standalone case at the nominal conditions.

Table 7.4: Leader SC economic summary (nominal conditions)

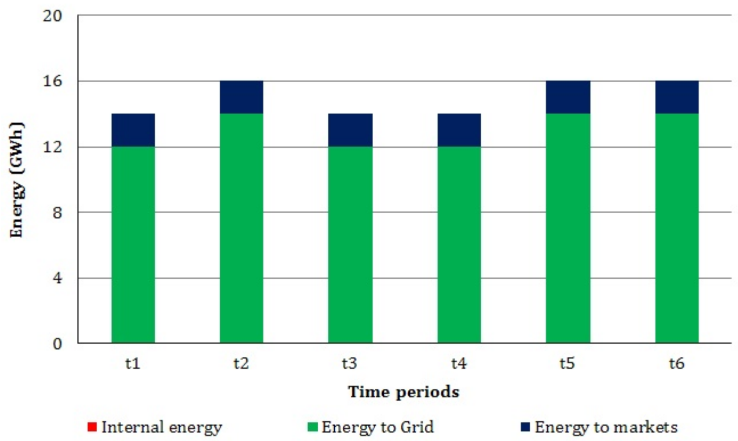
	Contract price: 0.185 m.u./kWh	Standalone
Cost (x10^6 m.u.)	10.52	11.12
Sales (x10^6 m.u.)	18.59	18.59
Profit (x10^6 m.u.)	8.07	7.47

7.6.3 Tactical decisions: Follower SC

It is noticed from Figure 7.15 that the coordination would lead the follower to generate 16.71 GWh more energy; 18.60 % more than the standalone case. It is also worth noticing that the energy sales to the local grid has been reduced by 11.4 % (8 GWh) due to the coordination contract (0.185 m.u./kWh to 24.71 GWh), comparing with the standalone case. In the standalone case, the follower has to sell 11.40 % (8 GWh) more energy to the local grid in order to compensate the lack of the coordination. However, the follower could not be able to sell higher amounts of energy to the local grid as the cost becomes higher and the market prices do not compensate.



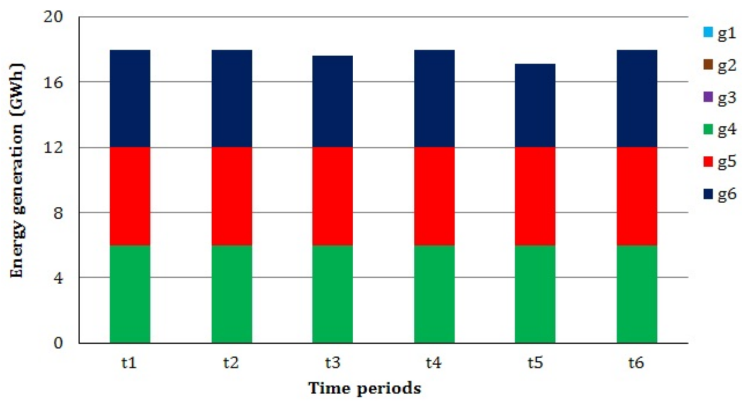
(a) Contract price: 0.185 m.u./kWh



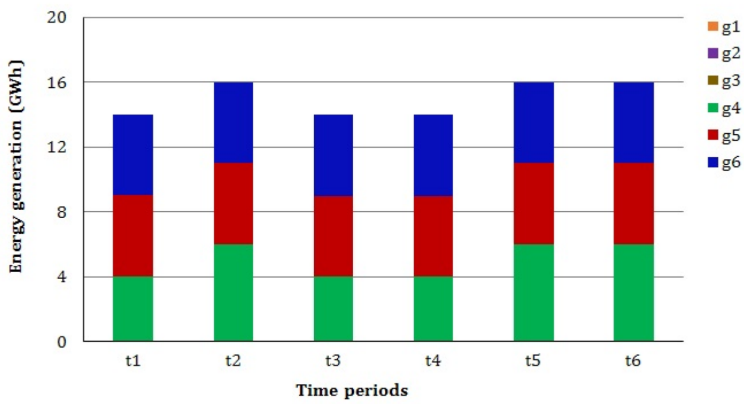
(b) Standalone

Figure 7.15: Follower SC energy sales

Figure 7.16 illustrates the energy generation activities along the planning horizon resulting from the coordination contract (0.185 m.u./kWh to 24.71 GWh) (Figure 7.16(a)) and the standalone case (Figure 7.16(b)). The coordination contract would lead to functioning the energy generation plants ($g4$, $g5$, and $g6$) up to their generation capacities (6 GWh) all time periods in order to sell 24.71 GWh to the leader SC. However, in the standalone case, the follower decides not to function the energy generation plants up to their generation capacities. The cost of generating 1GWh is high (0.17 m.u./kWh), and the local grid higher prices are restricted to lower energy amounts (Figure 7.9(a)) which does not compensate the follower.



(a) Contract price: 0.185 m.u./kWh

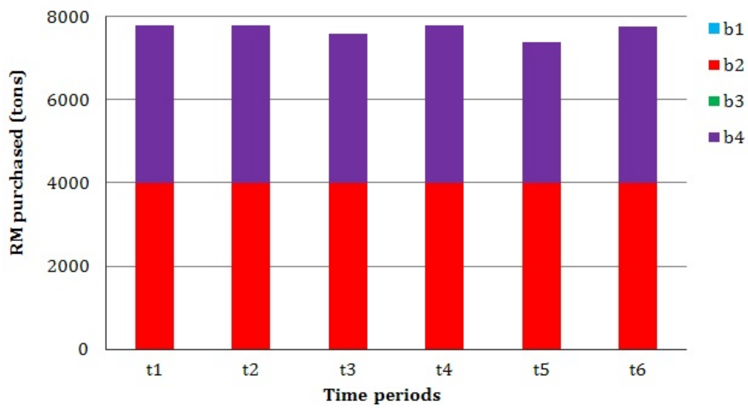


(b) Standalone

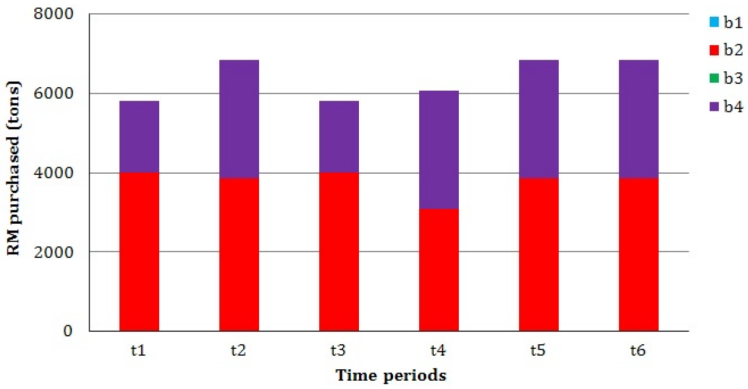
Figure 7.16: Energy generation levels

To understand this point; assume that the follower at the standalone case wants to sell the highest possible amount (up to energy generation capacities). The best option is to operate the energy generation plants ($g4$, $g5$, and $g6$). So, the maximum energy generation = 3 x 6 x 6 = 108 GWh to be distributed between the local grid as external client and the fixed energy markets. The energy sales to the energy markets = 12 GWh (fixed demand 2 GWh per time period). So, the sales to the local grid will be 96 GWh (16 GWh per time period). According to Figure 7.9(b), to sell higher energy amounts (more than 4 GWh), the price is 0.19 m.u./kWh. So, the energy economic sales = (96 x 0.19) + (12 x 0.20) = 20.60x10^6m.u. The cost of producing 108 GWh = 108 x 0.17 = 18.36x10^6m.u. This means that the follower SC payoff is equal to 2.24x10^6m.u., so the follower loses. And this explains why at the standalone case, the follower could not generate energy up to the generation capacity.

The follower SC RM purchase levels (Figure 7.17) follow the energy generation levels. The RMs $b2$ and $b4$ dominate the RM purchase levels due to their lower prices (see Table B.1). However, the coordination would lead to 20.8 % (7.94x10^3tons) higher RM purchase amounts in order to follow the higher levels of the energy generation.



(a) Contract price: 0.185 m.u./kWh



(b) Standalone

Figure 7.17: Follower RM purchase levels

Table 7.5 summarizes the follower economic decisions resulting from the coordination contract (24.71 GWh at 0.185 m.u./kWh) in comparison with the standalone case. The coordination contract achieves 17.8 % improvement in the total economic sales leading to 18.8 % increase in the follower SC cost and 11.48 % total gains.

Table 7.5: Follower SC economic summary (nominal conditions)

	Contract price: 0.185 m.u./kWh	Standalone
Cost (x10^6 m.u.)	18.27	15.38
Sales (x10^6 m.u.)	20.99	17.82
Profit (x10^6 m.u.)	2.72	2.44

7.6.4 Coordination under the follower uncertain conditions

The integrated GT outcome is evaluated under the uncertain conditions of the follower SC resulting from the uncertain nature of its third parties. To do so, the Stackelberg payoff matrix in Table 7.3 is evaluated using Monte-Carlo sampling method. The follower SC model is solved for 500 scenarios generated from each energy price policy of the third parties considering: mean (μ) = energy prices as in Table 6.1; standard deviation (σ) = 0.03. The expected payoffs of the follower are obtained. Here, the leader payoffs are not affected, as the uncertainty is considered just around the follower SC. Table 7.6 illustrates the

Stackelberg payoff matrix considering the leader payoffs and the follower expected payoffs. It is noticed that the expected follower payoff at the standalone case (2.74x10^6 m.u.) increases; 12.20 % more than its standalone nominal payoff (2.44x10^6m.u.).

The Stackelberg leader payoff-follower expected payoff matrix is represented in Figure 7.18. The leader standalone payoff and the follower expected standalone payoff are obtained to mark the winning zone. It is noticed that the follower expected standalone payoff has been shifted by 0.29x10^6m.u. to the right side, in comparison with Figure 7.6. This means that the leader has to offer higher prices in order to compensate the follower in case of any possible disruptions. The follower is expected to gain more under her/his uncertain conditions, and thus his/her expectations from the leader becomes higher, excluding the leader price offer 0.17 m.u./kWh from the game (it becomes inside the losing zone of the follower). The new win-expected win zone starts from the leader price 0.18 m.u./kWh (Figure 7.18).

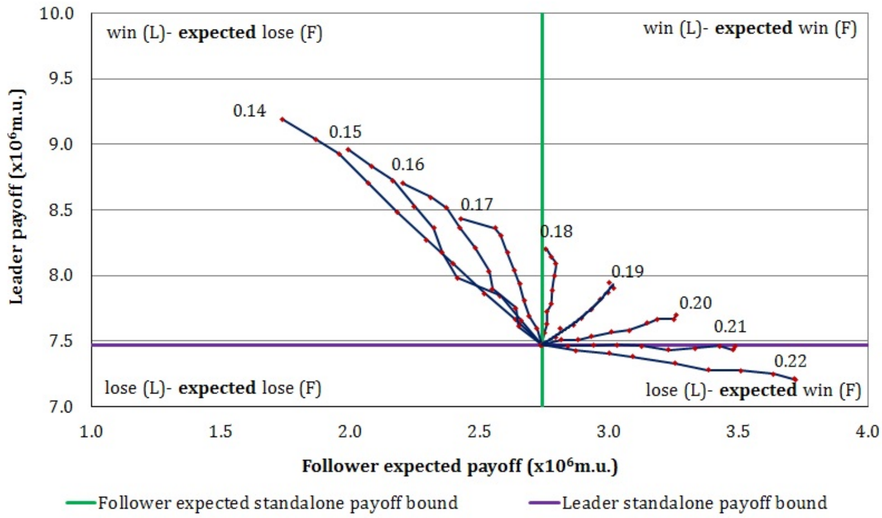


Figure 7.18: Leader payoff vs. follower expected payoff

Table 7.6: Stackelberg payoff matrix (follower uncertainty)

	Leader (L) payoff vs. follower (F) **expected** payoff (x10^6 m.u.)																	
Leader action (m.u/kWh) →	0.14		0.15		0.16		0.17		0.18		0.19		0.20		0.21		0.22	
Follower reaction (GWh)↓	F	L	F	L	F	L	F	L	F	L	F	L	F	L	F	L	F	L
0	2.74	7.47	2.74	7.47	2.74	7.47	2.74	7.47	2.74	7.47	2.74	7.47	2.74	7.47	2.74	7.47	2.74	7.47
3.00	2.64	7.66	2.66	7.66	2.65	7.61	2.72	7.59	2.75	7.57	2.79	7.53	2.81	7.51	2.84	7.46	2.87	7.43
6.00	2.52	7.87	2.58	7.85	2.64	7.75	2.69	7.69	2.76	7.63	2.81	7.60	2.88	7.51	2.94	7.47	3.00	7.41
9.00	2.40	8.09	2.41	7.98	2.55	7.90	2.67	7.81	2.76	7.72	2.86	7.63	2.93	7.54	3.03	7.47	3.09	7.38
12.00	2.29	8.27	2.35	8.17	2.53	8.04	2.65	7.94	2.78	7.79	2.89	7.67	3.01	7.57	3.13	7.46	3.25	7.33
15.00	2.18	8.48	2.32	8.36	2.48	8.21	2.63	8.04	2.78	7.89	2.93	7.74	3.08	7.58	3.23	7.43	3.38	7.28
18.00	2.07	8.71	2.25	8.53	2.42	8.36	2.61	8.18	2.79	8.00	2.97	7.82	3.15	7.64	3.33	7.45	3.51	7.28
21.00	1.96	8.93	2.16	8.72	2.37	8.52	2.58	8.31	2.79	8.09	2.99	7.87	3.19	7.67	3.43	7.46	3.64	7.25
23.10	1.86	9.04	2.08	8.83	2.31	8.60	2.56	8.36	2.78	8.14	3.02	7.91	3.25	7.67	3.48	7.44	3.71	7.21
24.71	1.74	9.19	1.99	8.96	2.20	8.70	2.43	8.43	2.76	8.21	3.00	7.95	3.26	7.70	3.49	7.46	3.72	7.21

Then, a different set of leader prices offers are examined between 0.18 m.u./kWh and 0.21 m.u./kWh, and the leader win and the follower expected win payoffs are obtained (Figure 7.19). The Stackelberg set of "Pareto frontier" is established for each scenario; in which each point corresponds to a possible coordination contract. Comparing with the payoffs under the nominal conditions of Figure 7.7, it can be seen that the leader price offers 0.175 and 0.178 m.u./kWh are also excluded from the game.

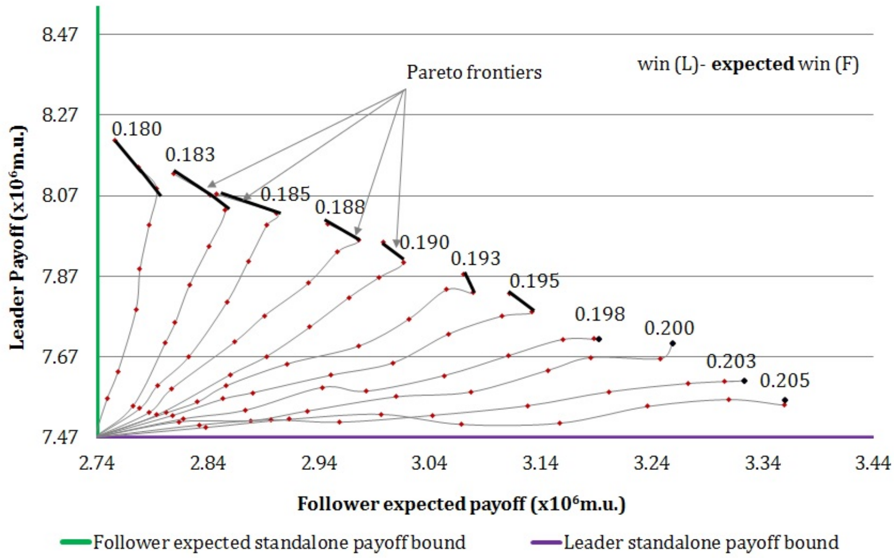


Figure 7.19: Leader win-follower expected win solutions

The Stackelberg set of "Pareto frontier" under the follower uncertain conditions can be established if the leader's offers are between 0.18 m.u./kWh and 0.205 m.u./kWh (Figure 7.20) and the follower response is between 23.10 and 24.71 GWh. In any of these cases, the follower shall be able to offer between 23.10 GWh and 24.71 GWh to the leader with a significant profit potential respect to the standalone case, the leader would also gain from this deal.

Figure 7.21 shows the follower nominal/expected payoffs. Here, it can be seen clearly the positive shift of the follower expected payoff up to its nominal payoff; an increase of 12.2 % (0.29x10^6m.u.) of the follower expected standalone payoff leads to 6.6 % increase in the follower profit expectations. This results in excluding the prices offers (> 0.18 m.u./kWh).

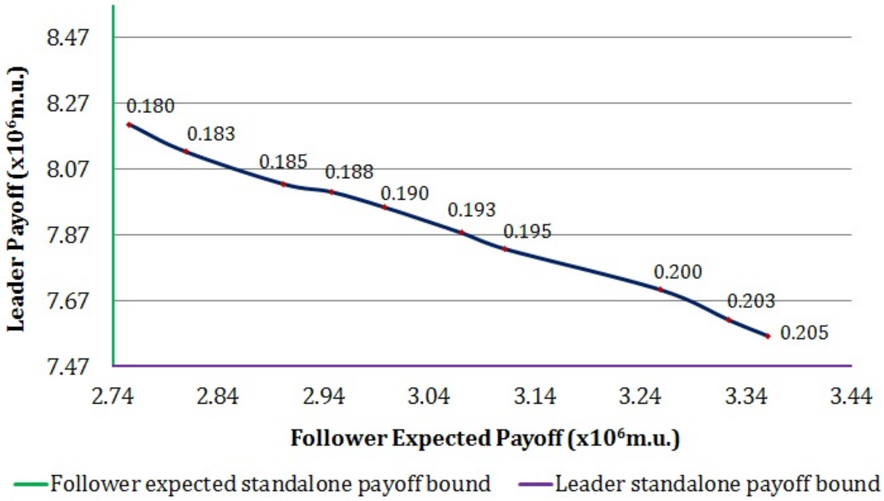


Figure 7.20: Leader win-follower expected win solutions

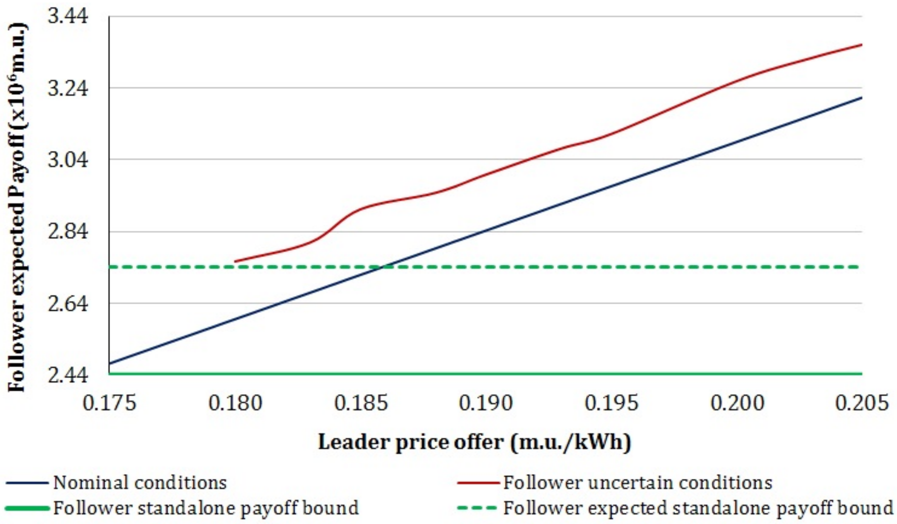


Figure 7.21: Follower nominal vs. expected payoffs

Follower uncertainty reduction effects

The probability of acceptance of the follower is calculated for each coordination contract possibility. The variance (σ^2) of the follower expected payoffs is calculated and plotted on Figure 7.22. It is noticed that the probability of acceptance increases when the leader price offers increase, resulting in higher expectations of the follower payoffs. It is worth noticing that the coordination reduces the variance of the follower expected payoff by 27.34 % comparing with the variance at the expected standalone case. The variance using the different coordination contracts is not the same, as the internal energy amounts (contract amounts) are not the same; lower energy amounts lead to higher uncertainty and thus to higher variance in the profits scenarios. This means that the coordination guarantee an "uncertainty effect reduction" of the expected payoffs of the follower (expected payoff = contract payoff + market payoff). The coordination assures stable benefits regardless of the uncertain conditions along the planning time horizon (Figures 7.22 and 7.23). Such market stability stresses the willingness of the game players to collaborate taking into consideration that both of them can improve the quality of their SCs, such as reducing operational cost so to assure higher benefits than what they get from the coordination contract.

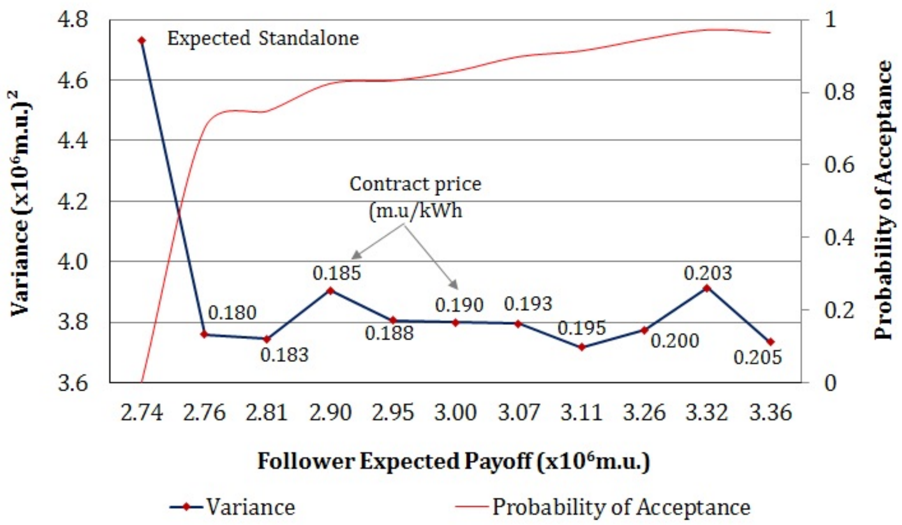


Figure 7.22: Probability of acceptance and variance (Follower uncertain conditions)

Figure 7.23 shows the breakdown of the expected payoff of the follower under the different coordination contracts. It is to be noticed that the standalone case results in zero uncertainty effect reduction which is risky for the follower. However, the uncertainty effect reduction increases (lower variance) when the coordination contract prices increase.

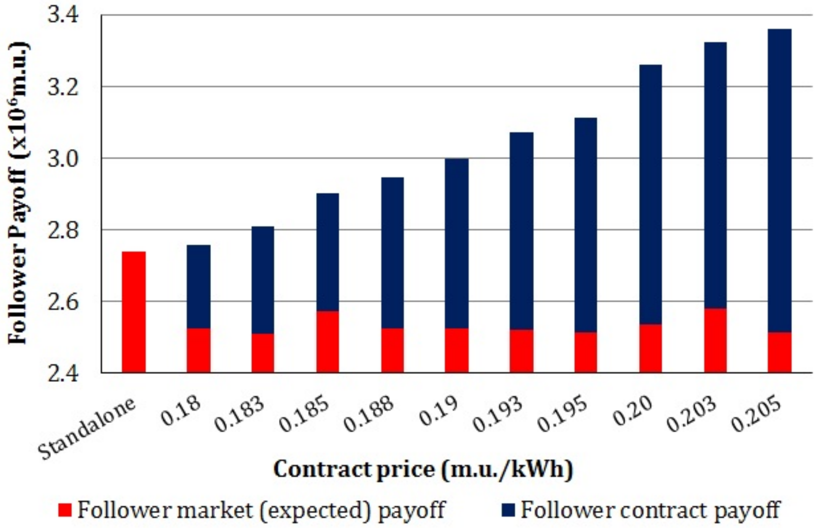


Figure 7.23: Follower contract and market payoffs (follower uncertain conditions)

7.6.5 Stackelberg vs. SBDN approach

The results obtained in this chapter using the integrated game theory approach are compared with the results obtained in Chapter 6 using the scenario-based dynamic negotiations (SBDN) under the uncertainty of the follower partner. Using the SBDN, the best coordination contract offered by the leader under the uncertainty of the follower corresponds to the transfer price 0.18 m.u./kWh for 24.71 GWh. This solution is the same best solution resulting in this chapter (see Table 7.6 & Figure 7.20). Table 7.7 summarizes the coordination contract results (transfer price 0.18 m.u./kWh for 24.71 GWh) from the SBDN and the integrated GT approach. It is noticed that the integrated GT approach leads to better follower expected payoff with a difference of 1.7 % comparing with the SBDN approach.

Table 7.7: Comparison: SBDN vs. integrated game theory

		SBDN (Chapter 6)		Integrated GT (this chapter)	
Contract price (m.u./kWh)	Contract energy (GWh)	Leader payoff ($\times10^6$m.u.)	Follower expected payoff ($\times10^6$m.u.)	Leader payoff ($\times10^6$m.u.)	Follower expected payoff ($\times10^6$m.u.)
0.18	24.71	8.23	2.71	8.21	2.76

Unlike the SBDN, the contracted energy supply (Figure 7.24) corresponds to the optimal amounts that the follower decides according to her/his best conditions leading to higher expected payoffs. On the contrary, for the SBDN, the leader decides the energy flows at each time period (Figure 7.25) according to her/his best expected conditions based on the probability of acceptance of the follower. This is why the SBDN leads to 0.02x10^6m.u. more gains for the leader SC in 6 time periods, in comparison with the integrated GT approach.

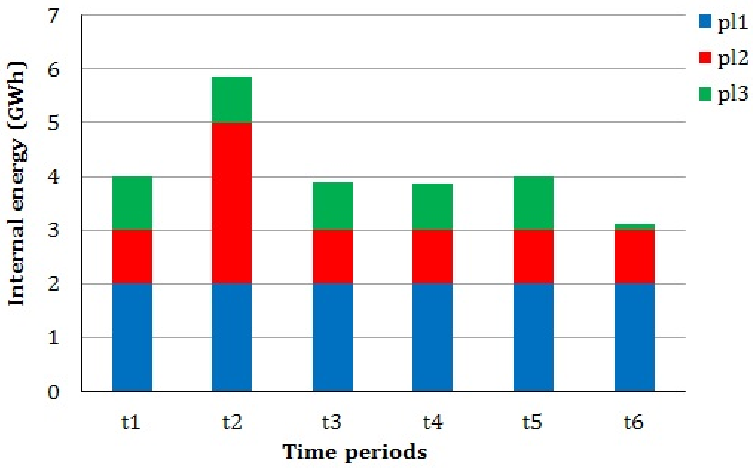


Figure 7.24: Internal energy flows using integrated GT at price 0.18 m.u./kWh

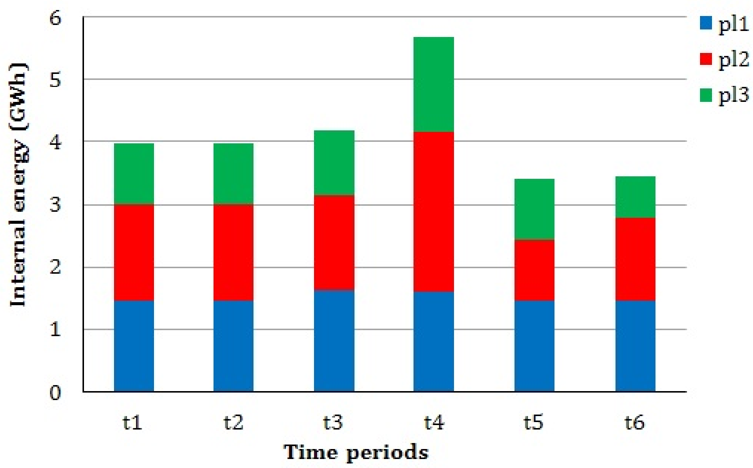


Figure 7.25: Internal energy flows using SBDN at price 0.18 m.u./kWh

7.6.6 Coordination under the leader uncertain conditions

In this section, the Stackelberg payoff matrix at the nominal conditions is evaluated considering the uncertain behavior of the (game leader). The MINLP tactical model of the leader SC is solved for the generated 500 scenarios of the local grid price policy using Monte-Carlo sampling method: mean (μ = local grid energy prices as in Table 7.1; standard deviation (σ) = 0.03. Table 7.8 illustrates the Stackelberg payoff matrix considering the leader expected payoffs and the follower nominal payoffs for each coordination contract offer. It can be noticed that the coordination would lead to 6.80 % (0.50x10^6 m.u.) higher leader expected payoffs at the standalone case (7.98x10^6 m.u.) comparing with its nominal standalone payoff (7.47x10^6 m.u.).

Given that the expected standalone payoff of the leader is higher than its nominal standalone payoff, and that unlike the case of the follower, the leader has to offer lower prices (Figures 7.26). The winning zone at the nominal, follower uncertain conditions, and leader uncertain conditions is summarized as below:

- 0.17 m.u./kWh $<$ Winning zone "nominal conditions" $<$ 0.21 m.u./kWh (Figure 7.6).
- 0.18 m.u./kWh $<$ Winning zone "follower uncertain conditions" $<$ 0.21 m.u./kWh (Figure 7.18).
- 0.17 m.u./kWh $<$ Winning zone "leader uncertain conditions" $<$ 0.19 m.u./kWh (Figure 7.26).

Here can be seen the contrasting objectives under the leader and the follower uncertain conditions, as the leader offers higher prices and the follower seeks lower prices.

Table 7.8: Stackelberg payoff matrix (leader uncertainty)

	Leader (L) **expected** payoff vs. follower (F) payoff (x10^6 m.u.)																	
Leader action (m.u/kWh) →	0.14		0.15		0.16		0.17		0.18		0.19		0.20		0.21		0.22	
Follower reaction (GWh)↓	F	L	F	L	F	L	F	L	F	L	F	L	F	L	F	L	F	L
0	2.44	7.98	2.44	7.98	2.44	7.98	2.44	7.98	2.44	7.98	2.44	7.98	2.44	7.98	2.44	7.98	2.44	7.98
3.00	2.36	8.13	2.41	8.10	2.43	8.06	2.46	8.04	2.50	8.01	2.51	7.98	2.54	7.95	2.59	7.92	2.62	7.88
6.00	2.29	8.27	2.35	8.22	2.41	8.16	2.47	8.09	2.53	8.04	2.59	7.98	2.65	7.92	2.71	7.86	2.77	7.80
9.00	2.20	8.43	2.29	8.32	2.37	8.24	2.46	8.15	2.56	8.07	2.64	7.98	2.74	7.88	2.83	7.80	2.91	7.71
12.00	2.10	8.56	2.22	8.44	2.34	8.32	2.46	8.21	2.58	8.08	2.70	7.95	2.82	7.84	2.94	7.72	3.06	7.60
15.00	2.01	8.71	2.16	8.56	2.31	8.41	2.46	8.26	2.61	8.11	2.76	7.96	2.91	7.81	3.06	7.66	3.21	7.51
18.00	1.89	8.86	2.07	8.68	2.25	8.50	2.43	8.32	2.61	8.14	2.79	7.96	2.97	7.78	3.15	7.60	3.33	7.42
21.00	1.77	9.02	1.98	8.82	2.19	8.60	2.40	8.39	2.61	8.18	2.82	7.96	3.03	7.76	3.24	7.55	3.45	7.34
23.10	1.69	9.12	1.92	8.88	2.15	8.65	2.38	8.42	2.62	8.19	2.85	7.96	3.08	7.72	3.31	7.49	3.54	7.27
24.71	1.61	9.19	1.85	8.96	2.10	8.70	2.35	8.43	2.60	8.21	2.84	7.95	3.09	7.70	3.34	7.46	3.58	7.21

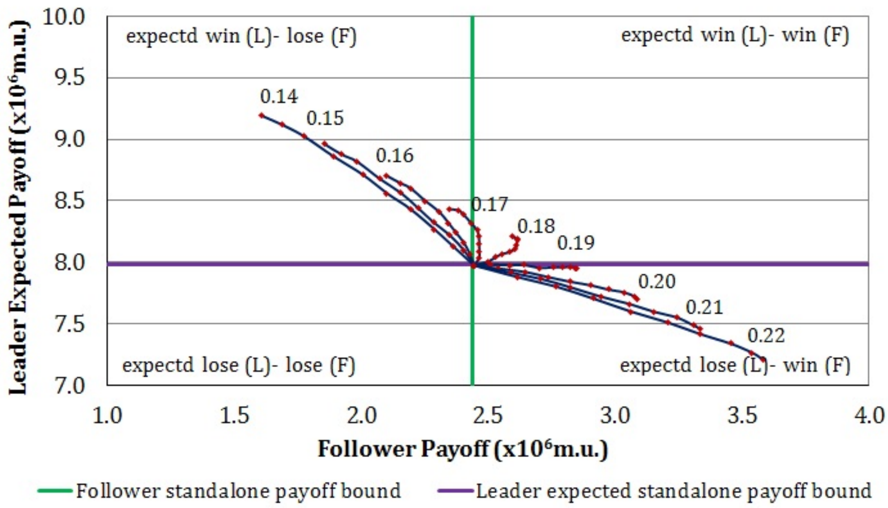


Figure 7.26: Leader expected payoffs vs. follower payoffs

Different sets of contract price offers are examined within the winning zone under the leader uncertain conditions to obtain the leader expected win and follower win payoffs (Figure 7.27). Different sets of "Pareto frontiers" are established for each leader price offer. Comparing with the nominal payoffs in Figure 7.7, the uncertain conditions of the leader SC bring the price 0.173 m.u./kWh into the game while excluding the prices (0.19-0.205 m.u./kWh).

The trade-off between the players payoffs under the uncertain conditions of the leader player is represented as Stackelberg set of "Pareto frontier" (Figure 7.28). In any of the solution points, the follower shall be able to offer between 23.10 GWh and 24.71 GWh to the leader with a significant profit potential respect to her/his standalone case, the leader would also obtain expected benefits from this deal. The similar prices on the Pareto frontier correspond to different contract energy amounts (23.10-24.71 GWh).

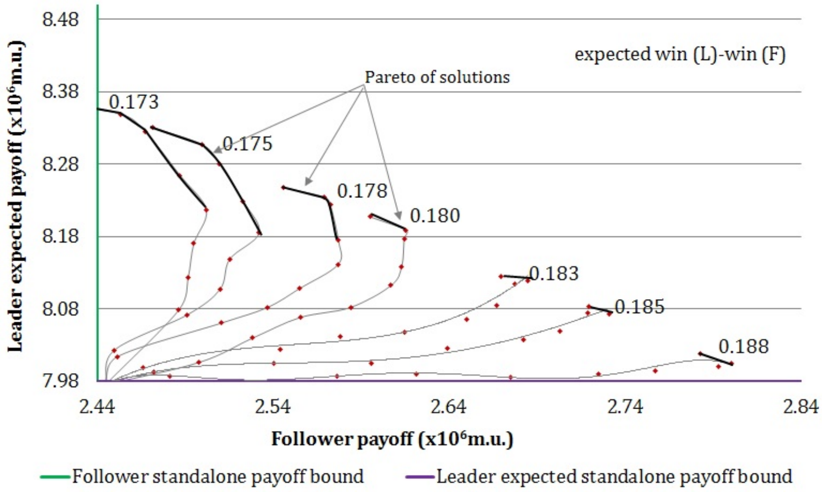


Figure 7.27: Leader expected payoffs vs. follower payoffs

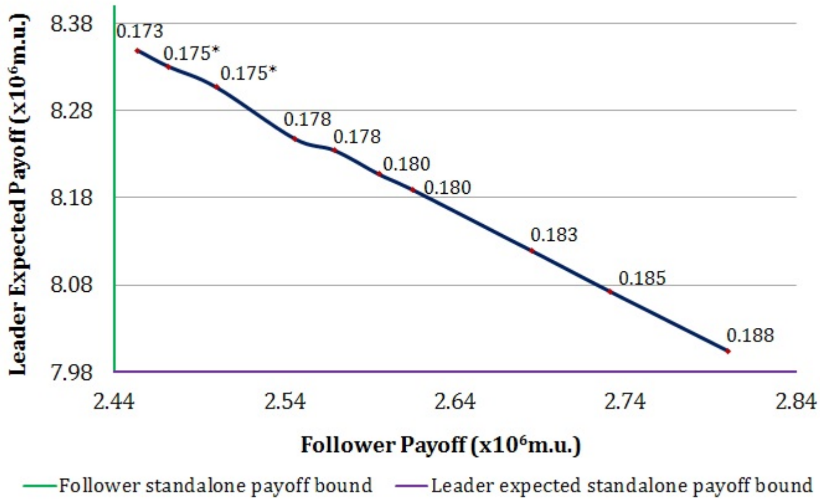


Figure 7.28: Leader expected payoffs vs. follower payoff. * Similar prices correspond to different energy amounts

Leader uncertainty effect reduction

The variances (σ^2) of the leader expected payoffs under the coordination contracts (resulted from the Stackelberg set of "Pareto frontier" are obtained together with the leader expected standalone payoff (Figure 7.29). It is noticed that the coordination would reduce the uncertainty effect that the leader may face, as the variances of the expected payoffs decrease from 0.50 (x10^6 m.u.)^2 to almost zero. This means that the coordination guarantee a confident payoff "contract payoff" whatever is the uncertain market situation around the leader SC.

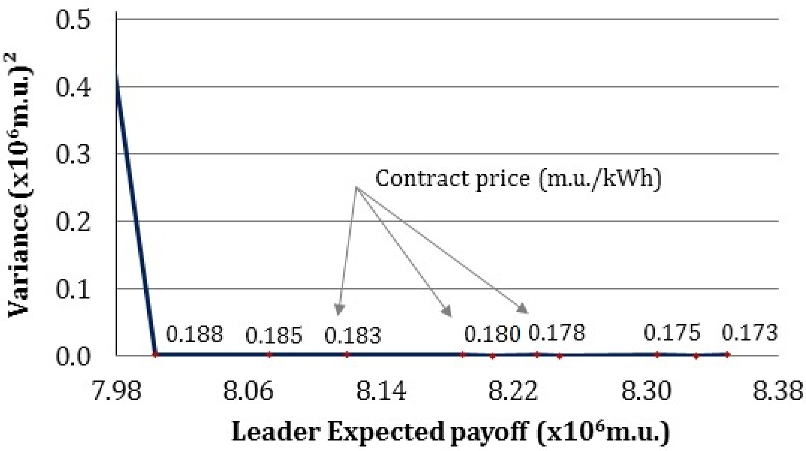


Figure 7.29: Leader expected payoffs variance

7.6.7 Coordination under uncertainty of all participants

The Stackelberg payoff matrix at the nominal conditions (Table 7.3) is evaluated considering the uncertain behavior of the leader and the follower game players resulting from the uncertain nature of their competitive third parties. Then, the Stackelberg expected payoff matrix is built for the expected payoff leader-follower (Table 7.9). It is noticed that the coordination under both game players uncertain conditions would lead to 6.80 % higher leader expected standalone payoffs (7.98x10^6 m.u.) comparing with the nominal standalone payoff (7.47x10^6 m.u.). Also, the coordination leads to 12.20 % increase in the follower expected standalone payoff comparing with the standalone nominal payoff (2.44x10^6 m.u.), in 6 time periods.

Table 7.9: Stackelberg expected payoff matrix (leader and follower uncertainty)

	Leader (L) **expected** payoff vs. follower (F) **expected** payoff (x10^6 m.u.)																	
Leader action (m.u/kWh) →	0.14		0.15		0.16		0.17		0.18		0.19		0.20		0.21		0.22	
Follower reaction (GWh)↓	F	L	F	L	F	L	F	L	F	L	F	L	F	L	F	L	F	L
0	2.74	7.98	2.74	7.98	2.74	7.98	2.74	7.98	2.74	7.98	2.74 7.98	2.74	7.98	2.74	7.98	2.74	7.98	
3.00	2.64	8.13	2.66	8.10	2.65	8.06	2.72	8.04	2.75	8.01	2.79	7.98	2.81	7.95	2.84	7.92	2.87	7.88
6.00	2.52	8.27	2.58	8.22	2.64	8.16	2.69	8.09	2.76	8.04	2.81	7.98	2.88	7.92	2.94	7.86	3.00	7.80
9.00	2.40	8.43	2.41	8.32	2.55	8.24	2.67	8.15	2.76	8.07	2.86	7.98	2.93	7.88	3.03	7.80	3.09	7.71
12.00	2.29	8.56	2.35	8.44	2.53	8.32	2.65	8.21	2.78	8.08	2.89	7.95	3.01	7.84	3.13	7.72	3.25	7.60
15.00	2.18	8.71	2.32	8.56	2.48	8.41	2.63	8.26	2.78	8.11	2.93	7.96	3.08	7.81	3.23	7.66	3.38	7.51
18.00	2.07	8.86	2.25	8.68	2.42	8.50	2.61	8.32	2.79	8.14	2.97	7.96	3.15	7.78	3.33	7.60	3.51	7.42
21.00	1.96	9.02	2.16	8.82	2.37	8.60	2.58	8.39	2.79	8.18	2.99	7.96	3.19	7.76	3.43	7.55	3.64	7.34
23.10	1.86	9.12	2.08	8.88	2.31	8.65	2.56	8.42	2.78	8.19	3.02	7.96	3.25	7.72	3.48	7.49	3.71	7.27
24.71	1.74	9.19	1.99	8.96	2.20	8.70	2.43	8.43	2.76	8.21	3.00	7.95	3.26	7.70	3.49	7.46	3.72	7.21

The expected standalone payoffs of the game players delimit the zone where the winning is expected (Figure 7.30). It can be seen that when both conditions of uncertainty are in force, this zone becomes reduced to contract prices from 0.18 m.u./kWh to 0.19 m.u./kWh.

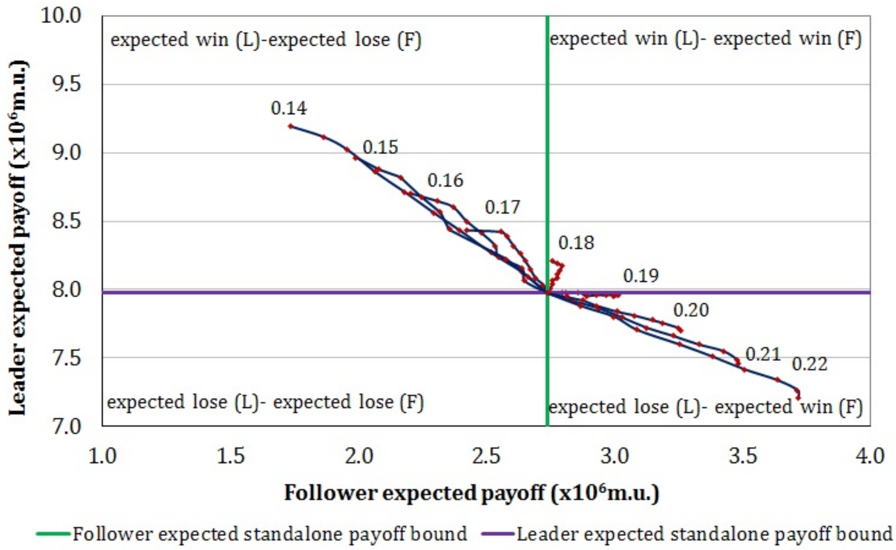


Figure 7.30: Leader expected payoffs vs. follower expected payoffs

The Stackelberg set of "Pareto frontier" is obtained (Figure 7.31) when the leader and the follower act under uncertain conditions. In any of these solution points, shall the follower offer the energy amounts between 21.00 GWh and 24.71 GWh to the leader with a significant profit expectations respect to the expected standalone case, the leader would also obtain expected benefits from this deal in case she/he offers prices from 0.18 m.u./kWh to 0.188 m.u./kWh. The rest of the energy amounts needed for the production SC of the leader is to be supplied from the local grid. The similar prices on the Pareto frontier correspond to different energy contract amounts.

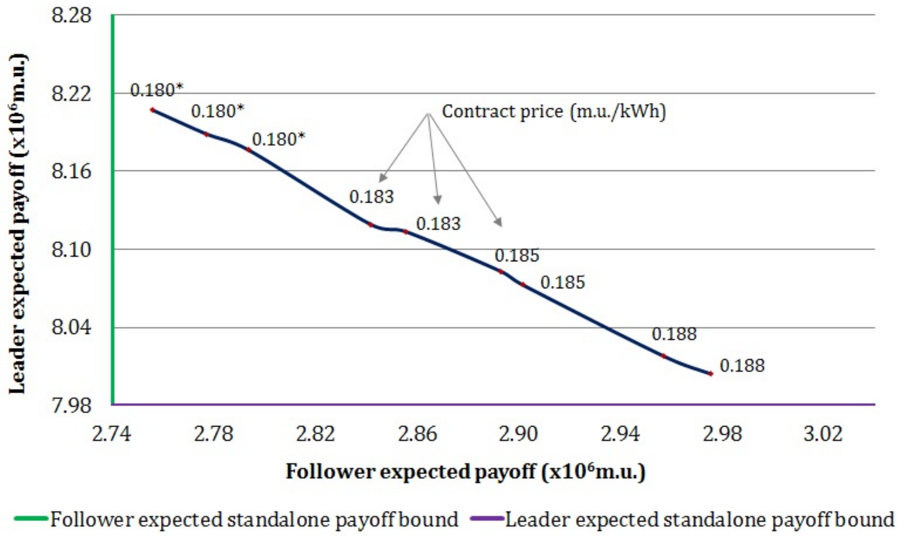


Figure 7.31: Stackelberg set of Pareto frontier under leader and follower uncertain conditions. * Similar prices correspond to different energy amounts

Table 7.10 summarizes the possible coordination contracts based on the different uncertain conditions. It should be noticed, as it is mentioned in the above sections, that each game player seeks its SC individual nominal/expected benefits; the follower seeks higher prices and the leader seeks lower prices. And when considering the uncertain conditions of both of them, a compromise can be reached for the trade-off between their expected payoffs, excluding the lower prices less than 0.18 m.u./kWh from the follower side, and the prices greater than 0.188 m.u./kWh from the leader side.

Table 7.10: Coordination contracts summary

	Coordination contract	
	Price (m.u./kWh)	Energy amount (GWh)
Nominal conditions	0.175-0.205	24.71
Follower uncertain condition	0.18-0.205	23.10-24.71
Leader uncertain conditions	0.173-0.188	23.10-24.71
Leader and follower uncertain conditions	0.18-0.188	21.00-24.71

From all the above-mentioned cases, the uncertain behavior of the game players affects the trade-off between their payoffs, and thus affects the equilibrium of the whole system. Each coordination contract is able to mitigate the uncertainty of the third parties resulted from the dynamic market situation. The coordination proves to be viable under the nominal and uncertain conditions, thus stressing the SCs enterprises stakeholders willingness to collaborate and negotiate the different proposed solutions

7.7 Switching the game players roles

The coordination/collaboration contracts in the above mentioned sections are obtained considering that the manufacturer (client) is the game leader. However, in this section, the analysis of the decisions obtained when the roles of the game players are switched, in which the client is dealt as the follower game player, is analyzed. The provider as the game leader offers the coordination contract price and the client as the game follower responds with the required energy amounts along the planning horizon (reaction function).

As in the opposite case, at the nominal conditions, the Stackelberg payoff matrix is built (Table 7.11 and Figure 7.32) for the presented case study. It is noticed that, unlike Table 7.3, the coordination contract price offer starts from 0.22 m.u./kWh. The follower player in this case is the provider, in which she/he will try higher prices first.

Compared with Figure 7.6 at the same nominal conditions, Figure 7.32 shows that switching the roles of the game players leads to exclude the coordination contract price 0.17 m.u./kWh from the game. At price 0.17 m.u./kWh, before switching the roles (Table 7.3), the provider payoff as follower is 2.35x10^6 m.u.; 7.8% more than when switching the roles (Table 7.11) for the same energy amount (24.71 GWh). This is because the follower is the one who decides the internal energy flows (reaction function) according to its SC best conditions.

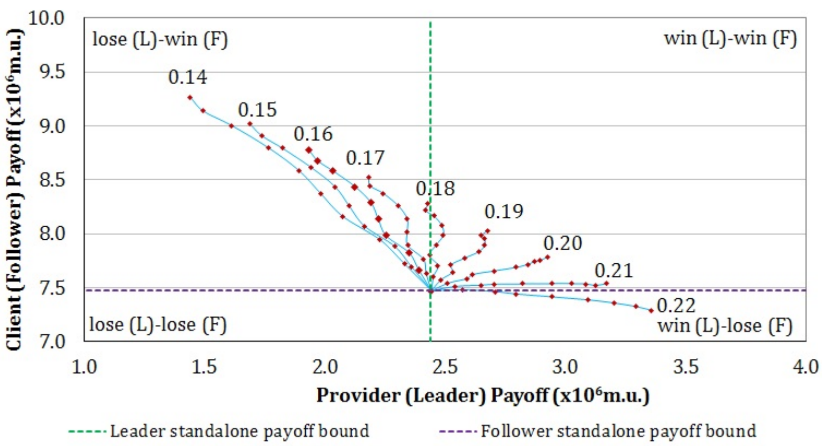


Figure 7.32: Leader vs. follower payoffs

Table 7.11: Stackelberg payoff matrix (switched roles)

	Leader (L) payoff vs. follower (F) payoff (x10^6 m.u.)																	
Leader action (m.u/kWh) →	0.22		0.21		0.20		0.19		0.18		0.17		0.16		0.15		0.14	
Follower reaction (GWh)↓	F	L	F	L	F	L	F	L	F	L	F	L	F	L	F	L	F	L
0.00	7.47	2.44	7.47	2.44	7.47	2.44	7.47	2.44	7.47	2.44	7.47	2.44	7.47	2.44	7.47	2.44	7.47	2.44
3.00	7.48	2.57	7.51	2.54	7.54	2.51	7.57	2.48	7.60	2.45	7.63	2.42	7.66	2.39	7.69	2.36	7.72	2.33
6.00	7.46	2.71	7.52	2.65	7.58	2.59	7.64	2.53	7.70	2.47	7.76	2.41	7.82	2.35	7.88	2.29	7.94	2.23
9.00	7.44	2.80	7.53	2.71	7.62	2.62	7.71	2.53	7.80	2.44	7.89	2.35	7.98	2.26	8.07	2.17	8.16	2.08
12.00	7.41	2.94	7.53	2.82	7.65	2.70	7.77	2.58	7.89	2.46	8.01	2.34	8.13	2.22	8.25	2.10	8.37	1.98
15.00	7.39	3.09	7.54	2.94	7.69	2.79	7.84	2.64	7.99	2.49	8.14	2.34	8.29	2.19	8.44	2.04	8.59	1.89
18.00	7.36	3.21	7.54	3.03	7.72	2.85	7.90	2.67	8.08	2.49	8.26	2.31	8.44	2.13	8.62	1.94	8.80	1.77
21.00	7.32	3.29	7.53	3.08	7.74	2.87	7.95	2.66	8.16	2.45	8.37	2.24	8.58	2.03	8.79	1.82	9.00	1.61
23.10	7.29	3.36	7.52	3.13	7.75	2.90	7.98	2.65	8.21	2.42	8.44	2.19	8.68	1.97	8.91	1.74	9.14	1.50
24.71	7.29	3.42	7.54	3.17	7.78	2.93	8.03	2.68	8.28	2.43	8.52	2.18	8.77	1.94	9.02	1.69	9.27	1.44

The Stackelberg set of "Pareto frontier" is obtained from switching the roles (Figure 7.33). Compared with Figure 7.8 under the same nominal conditions, switching the roles leads to exclude lower prices 0.175-0.180 m.u./kWh from the game, and adding higher prices 0.208-0.210 into the game for the same reason explained in the above paragraph. This is due to the leading role of the provider, who seeks higher prices.

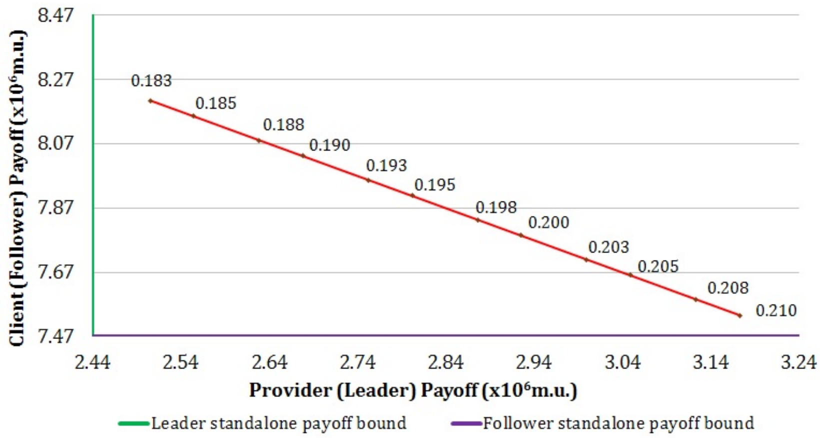


Figure 7.33: Stackelberg set of Pareto frontier

Figure 7.34 shows a comparison between the Stackelberg set of "Pareto frontiers" obtained from the original roles (client as leader: Figure 7.7) and from switching the roles (client as follower: Figure 7.33). Unexpectedly, the traditional myth of leading the game does not guarantee higher payoffs, although it affects the game outcome. According to the methodology of this chapter, the follower player decides the internal energy amounts (reaction function) along the planning horizon according to its SC best conditions.

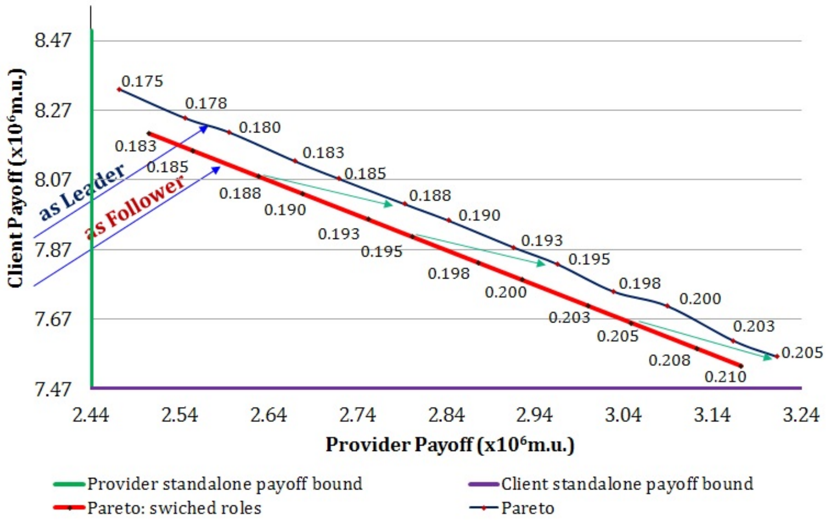


Figure 7.34: Stackelberg set of Pareto frontier: switching the game players roles

As it is noticed in Figure 7.35, the client role as follower leads to higher payoffs; ~ 1.32 % (100.74 x10^3m.u.) than when leading the game for the presented case study.

It is also noticed from Figure 7.36 that the provider role as follower leads to ~ 6.5 % higher payoffs than when leading the game.

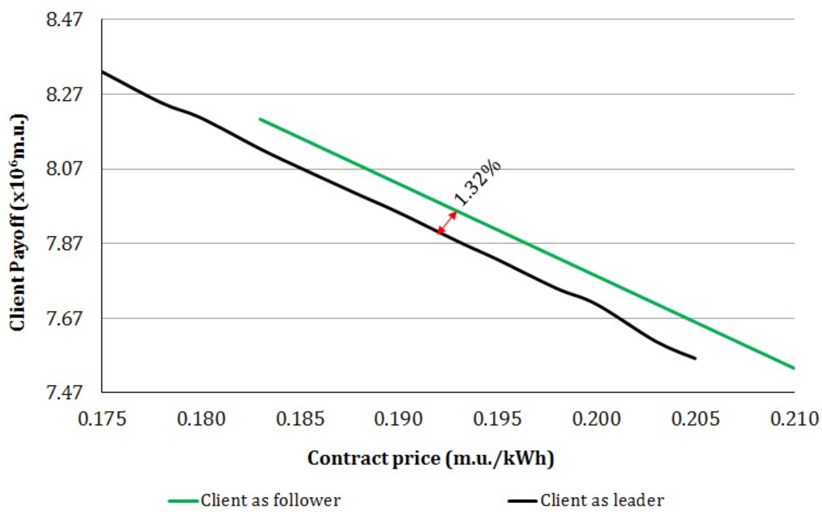


Figure 7.35: Client game role (Leader vs. follower)

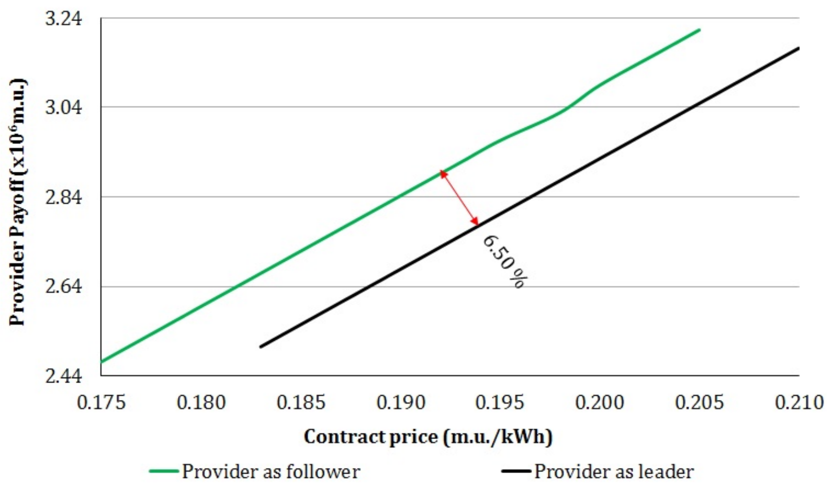


Figure 7.36: Provider game role (Leader vs. follower)

Unlike the traditional myth of being the leader, leading the game does not guarantee higher revenues. The game revenues depend not only on the game players roles, but also on the reaction function, which marks the difference.

7.8 Final considerations

This chapter presents an integrated Game Theory (GT) method as a decision-support tool for Multi Enterprise-Wide Coordination (M-EWC) by determining the best coordination/collaboration between the enterprises with contrasting and competitive objectives participating in a multi-enterprise multi-echelon multi-product SC network under uncertainty.

Based on non-symmetric roles, the interaction between the enterprises with contrasting objectives is modeled as non-cooperative non-zero-sum Stackelberg-game under the leading role of the manufacturer (client). The methodological framework of the Stackelberg-game is based on building the payoff matrix under the nominal conditions. This payoff matrix then is evaluated using Monte-Carlo sampling method by considering: i) the uncertain conditions of the follower, ii) the uncertain conditions of the leader, and iii) the uncertain conditions of both game players resulting from the uncertain nature of their competitive third parties, so that the Stackelberg **expected** payoff matrix is built. The competitions between the clients (on one side) and between the providers (on the other side) are solved using Nash Equilibrium (NE) games, in which the Stackelberg-game players (client and provider) are modeled as competitive NE-game players with the external clients and the external providers (third parties).

The integrated GT outcome is represented as a novel Stackelberg set of "Pareto frontier", where each solution point is a **Stackelberg-NE equilibrium** coordination contract. The resulting coordination contracts are able to mitigate the uncertainty effects of external conditions associated to each one of the game players while keeping their expectations of potential of higher profits, compared to their respective standalone cases. Furthermore, the integrated-GT tactical model formulation is generic and flexible enough to be applied when different clients and different providers participate in a decentralized large-scale SC network.

The game players roles have been switched to study their effect on the game outcome. The results on the presented case study show that, the traditional myth of leading the game does not guarantee higher payoffs, although it affects the game outcome. The game player role as follower rather than as leader results in higher payoffs. The game revenues depend not only on the game players roles, but also on the reaction function, which marks the difference.

In summary, the results show that efficient coordination is able to reduce the risks that each game player may face due to the volatile markets, thus stressing their willingness to collaborate under extreme conditions. The flexibility of the generic model and its ability to contain all possible SCs (centralized/decentralized, standalone/non-cooperative) including the third parties SCs add to the PSE and OR researches a new comprehensive approach able to solve complex decentralized decision-making structures, allowing all possible links and nodes among all possible stakeholders.

7.9 Nomenclature

Indices

r	resource (raw material, product, energy, steam, cash,...)
r'	negotiation resources
sc	supply chain
t	time period
i	NE-game competitive providers
j	NE-game competitive clients

Sets

F	follower supply chain
L	leader supply chain
m	final customers
n	piecewise pricing zone
pl	production plants
R	resources (raw material, product, energy, steam, cash,...)
T	time period
w	warehouses/distribution centers
w'	external warehouses/distribution centers
C	external client SC
V	external provider SC

Parameters

$ST^{max}_{r',w',t}$	maximum storage capacity of resource r' at warehouse w', leader SC, time t
$ST^{min}_{r',w',t}$	minimum storage capacity of resource r' at warehouse w', leader SC, time t
$PRD^{min}_{r,pl,sc,t}$	minimum production of resource r in production plant pl, time t
$PRD^{max}_{r,pl,sc,t}$	maximum production of resource r in production plant pl, time t
$rp_{r,m}$	retail price of resource r (final product)
$vrm_{r,s,sc,t}$	unit price of resources r purchased from external suppliers s, time t
$uprd_{r,sc}$	unit production cost of resource r
$ust_{r,w,sc}$	unit storage cost of resource r in warehouse w
$dis_{r,sc}$	travel distance of the resource r, supply chain sc
$utr_{r,sc}$	unit transport cost of resource r, supply chain sc
$pC^{min}_{r',sc,t,n}$	minimum unit price of resource r', client sc C, price zone n, time t
$pC^{max}_{r',sc,t,n}$	maximum unit price of resource r', client sc C, price zone n, time t
μ	mean

σ	standard deviation

Continuous variables

X	upper-level decision variables
Y	lower-level decision variables
$G_L(x,y)$	upper-level inequality constraints
$H_L(x,y)$	upper-level equality constraints
$Z_L(x,y)$	upper-level objective function
$z_F(x,y)$	lower-level objective function
$g_F(x,y)$	lower-level inequality constraints
$h_F(x,y)$	lower-level equality constraints
k_i	strategy of player i
k_{-i}	strategy of the rest of the competitive players
f_i	objective function of player i
k^*_{-i}	optimal strategy of the rest of the competitive players $(-i)$
k^*_i	optimal strategy of player $(i$
q^*_F	optimal strategy of the follower as NE-game player
q_F	strategy of the follower as NE-game player
$pL_{r',sc}$	unit transfer price of the game item r'
$QF_{r',sc,t}$	amounts of resource r' from the follower SC each time period t
$pC_{r',sc,t}$	unit price of resource r', client sc C, time t
$VL_{r',sc,t}$	amounts of resource r' purchased from the external provider, time t
$FPRD_{r,r',pl,sc,t}$	production levels of resource r' from resource r, production plant pl, follower SC, time t
$f_{r,r',sc}$	production recipe of producing resource r' from resource r, follower Sc, time t
$QFL_{r',sc,w',t}$	amounts of resource r' from follower SC to each warehouse w' of the leader SC, time t
$Ldem_{r',pl,t}$	demand of resource r' by production plant pl, leader SC, time t
$FC_{r',sc,t}$	resource r' flows from the follower SC to the external clients SC C, time t
$xdem_{r,sc,m,t}$	final customer demand of resource r, time t
$MK_{r,w,sc,m,t}$	resources r flows from the warehouses w to the final customers m, time t
$ST_{r',w,sc,t}$	storage levels of r' at warehouse w, time t
$FPD_{r',pl,sc,t}$	production levels of r' in production plant pl, follower Sc, time t
$QFC_{r',w,sc,w',t}$	quantity flows of r' from warehouse w of the follower SC to the the warehouse w' of the external client C, time t
$QL_{r',w',w,sc,t}$	quantity flows of r' at warehouse w of the leader SC from the follower SC warehouses w', time t
$QVL_{r',w',w,sc,t}$	quantity flows of r' from the external provider warehouses w' to leader warehouses w, time t
$LPRD_{r',r,pl,sc,t}$	production levels of resource r (intermediate product, final product, etc.) from r' in production plants pl, leader SC, time t

$fac_{r',r,sc}$	production recipe of resource r from resource r', time t
$QFC_{r',w',w,sc}$	quantity flows of resource r' at the warehouses w of the client SC from the warehouses w' of the follower SC, time t
$CP_{w,pl,sc,t}$	quantity flows from warehouses w to production plants pl, client SC, time t
$QVL_{r',w,w',sc}$	quantity flows of r' from warehouses w of the external provider SC to the warehouses w' of the leader SC
$VP_{w,pl,sc,t}$	quantity flows from warehouses w to to production plants pl, provider SC, time t
$PRD_{r,pl,sc,t}$	production levels of resource r at production plant pl, time t
$PAYOFF_{sc}$	aggregated payoff, supply chain sc
$SALE_{sc}$	economic sales, supply chain sc
$COST_{sc}$	cost, supply chain sc
$VL_{r',sc,t}$	resources r' purchased from the external provider, leader SC, time t
$pV_{r',sc,t}$	unit price of resource r', provider sc V, time t
CPR_{sc}	production cost
CRM_{sc}	external resources purchase cost
CST_{sc}	storage cost
CTR_{sc}	distribution cost
$pC_{r',sc,t}$	unit price of resource r', client SC C, time t
$RM_{r,s,sc,t}$	resources r (i.e. RM) purchased from external suppliers s, time t
$Q_{r,sc,t}$	resources r flows, supply chain sc, time t
$FC_{r',sc,t,n}$	resource r', client sc C, price zone n, time t
$pC_{r',sc,t,n}$	unit price of resource r', client sc C, price zone n, time t
$ExPAYOFF_{sc}$	expected payoff
$PAYOFF_{sc,ns}$	profit scenario
$prob_{sc}$	probability of acceptance
SN_{sc}	number of payoffs successful scenarios
TN_{sc}	total number of generated scenarios (Monte-Carlo sampling)

Discrete variables

$x_{r',t,n}$	Binary variable for pricing zone n of resource r', time t

Part IV

Conclusions

Chapter 8

Conclusions and Future Work

8.1 Conclusions

A new room is opened in this thesis coined as "multi-enterprise wide coordination (M-EWC)" to help chemical industry enterprises to manage their supply chains (SCs) in the presence of different interacting participants under uncertain competitive situations. To fill this room, several decision-support tools and solution approaches are proposed and compared from centralized and decentralized decision-making perspectives considering cooperative and non-cooperative organizations, and taking into account the decisions of all participants. The advantages and the applicability of the different proposed novel approaches have been briefly highlighted along this document.

The first part of this thesis (Part I) is the welcoming part to the M-EWC room. Within Part I, Chapter 1 addresses the importance of this thesis through highlighting the necessity of effective global and inter-organizational coordination/collaboration among several enterprises involved in large-scale SC complex systems, with their overlapping, contrasting and competitive goals in highly uncertain and competitive circumstances. The main objectives of this thesis towards optimal M-EWC are listed at the end of this chapter followed by the thesis outline as a guiding map of this document.

Since M-EWC problems tackled in this thesis are complex systems, the necessity to quick decisions implies the use of efficient method and tools. Chapter 3 underlies the methods and tools used for developing the new models throughout this thesis. The theoretical concepts and implementations of these methods and tools in the chemical industry are discussed in details. This chapter also illustrates the decision-making approaches and solution methods considering uncertainty, multi-objective optimization, and game theory.

Extensive state-of-the-art review and challenges are discussed in Chapter 2. Since SCs coordination has become a spot subject recently, many research challenges are emerged from the current state-of-the-art, such as: i) the global coordination considering the detailed information of all participants; ii) optimal integration of the supporting external enterprises (i.e. raw materials and utilities suppliers, clients, waste and recovery systems, etc.); iii) inter-organizational coordination between several enterprises participating as complete SCs with their complex model structures in a global multi-enterprise SC network, including their competitive third parties under uncertainty; iv) coordination contract evaluation under uncertainty taking into consideration the variability of the profits scenarios and their probabilities; v) expected win-win global coordination/collaboration considering the decisions of all participants under uncertain and competitive circumstances.

In Part II, a global coordination based on cooperative systems of large-scale chemical industry SCs enterprises with the external supporting organizations is achieved from a tactical management point of view.

In Chapter 4, a global cooperative-based coordination framework is proposed considering the detailed description of the external supporting participants (third parties) SCs within a global coordinated SC network with multiple echelons. This proposed coordinated approach is compared with the non-coordinated traditional approach, which represents the interaction with the third parties as economic transactions usually considered as fixed parameters (prices, capacities, etc.). A generic coordinated tactical model is developed taking into consideration the detailed characteristics of all participants (main SC enterprise and third parties SC). Each enterprise is represented as complete multi-site multi-echelon multi-product SC when developing the global tactical model.

The results of the presented case study show that the behavior of each echelon of the global system leads to different tactical decisions, which allows to obtain better global performance, resulting in potential improvements in the overall cost of the coordinated system. Furthermore, the proposed coordination approach leads to less consumption of resources while meeting the same market requirements. Unlike the current literature reviewed in Chapter 2, this chapter constitutes an advance in PSE because of the flexibility of the proposed coordinated model and its ability to integrate the detailed information of all participants involved in the system of study towards better global objectives and optimal resource management. Thus, all participants are able to share responsibilities and future risks, so they can compete in the dynamic global market.

Later, this global coordination framework is extended in Chapter 5 to consider the price policies of the different competitive third parties surrounding the global coordinated SC of Chapter 4 as part of the new global system. A generic tactical coordinated model is proposed integrating the price policies of the third parties as part of the decision-making process. When solving the developed tactical models to a global multi-site multi-echelon SC case study of real data, the results show that incorporating the price policies of the third parties as part of the global decision-making process allows them to participate as business partners, and thus compete in the global market. Dealing with the pricing as a collaborative tool between the third parties and the enterprises decision-makers, rather than as fixed economic transaction, allows enough margins for the third parties to control their financial channels and economic flows with the global coordinated SC. This chapter proves the potential of the pricing decisions in improving the SCM efficiency.

Then, and since the real price policies of the third parties may be complex to model, different pricing approximation models are presented and compared to estimate these policies based on average fixed and discounted piecewise and polynomial approximations. The pricing approximation approaches result in different complex tactical models. These models have been implemented to a multi-echelon multi-product large-scale supply chain case study. The results show that the selection of the pricing approximation approach significantly affects the global coordination and the tactical decisions of the whole system. Additionally, the trend of the global decision-maker using the discounting pricing approximation models based on the piecewise and polynomial trends is to purchase higher amounts of external resources from the third parties in different time periods in order to get lower prices. This leads to extra production in order to cope with the high RM purchase levels, getting the advantage of the storage system to store the excess products for later distribution. Such a behavior results in different economic performance for all participants.

When compared with the SC real total costs resulting from the optimal amounts obtained from the pricing models and their corresponding real prices, according to the real policies, a piecewise pricing model leads to the best pricing approximations with significant savings in the total SC cost. Unlike the usual habit of average approximations, the average pricing model is not recommended, as it leads to the worst decisions with the highest total cost, in comparison with the other pricing approximation models.

Unlike the reviewed literature on SCs coordination, Part II proposes a global coordination framework, which is generic and flexible enough to allow all possible links and interaction channels with more enterprises willing to participate in the system.

However, the main argument arises here is if the different actors refuse to cooperate under a global objective function (Part II), especially when their SCs can function, profitability, as standalone systems. The last part of this thesis tackles this argument through inter-organizational coordination/collaboration from a decentralized decision-making perspective, based on non-cooperative systems, in comparison with the cooperative and the standalone systems.

Part III deals with optimizing global multi-enterprise SCs under the objective functions of different non-cooperative participants. In such a situation, enterprises seek individual objectives (possibly contrasting/competitive) without considering the uncertain behavior of the other participants and the way how they may react to the different decisions, especially when they are surrounded by third parties in a highly uncertain and competitive environment.

In Chapter 6, different decision-support and solution approaches are proposed to help SC managers in making effective decisions in a decentralized environment under uncertainty. The coordination is proposed considering cooperative, and non-cooperative systems, comparing with the standalone case. The results show that the coordination based on non-cooperative systems, considering the detailed characteristics of all participants as complete SCs, leads to higher individual revenues, although the cooperation would lead to better total performance, in comparison with the standalone systems.

A non-cooperative Scenario-Based Dynamic Negotiation (SBDN) approach is proposed for M-EWC coordination of multi-echelon multi-product SCs surrounded by competitive third parties of uncertain price policies. The interactions between the main enterprises SCs and the third parties are modeled through the pricing models proposed in Chapter 5. Looking for win-win situation, the contrasting objectives between the negotiating partners (provider and client) are captured through a non-zero-sum SBDN with non symmetric roles, under the leading role of the client partner (manufacturing SC).

The methodological framework is based on anticipating the follower possible reactions resulting from the uncertain behavior of the third parties, which are projected as probability of acceptance in the objective function of the leader model. This probability of acceptance, as a measure of the willingness to collaborate, is one of the main added values of this chapter: it captures the variations of the follower profits scenarios obtained under different uncertain circumstances (Monte-Carlo sampling). Another added value of this chapter is the assessment methodology: a novel methodology is presented to evaluate a set of possible coordination contracts based on different risk behaviors (risk-seeking, risk-neutral, and risk averse) considering the cumulative probabilities of the follower profits scenarios. Moreover, the proposed SBDN approach allows the negotiating partners to accept or reject the collaboration. This flexibility is an added value of this chapter as, unlike the reviewed literature, the leader partner is not given a monopolistic role to impose the collaboration.

The results of the presented case study show that using the SBDN approach, it is possible to obtain and manage high individual benefit expectations likely to be accepted by the negotiating partners. Furthermore, the results show the importance of the transfer price of the conflicting resource on the negotiation process, since a small increase in the transfer price significantly increases the successful profits scenarios of the follower partner with higher probabilities, in comparison with the standalone case. The selection of the coordination contract affects the individual decisions of all participants, and thus affects the economic performance of the whole system. This chapter adds to PSE a decision-support tool that is able to identify expected win-win coordination. It allows all possible interactions and business channels with more participants.

The resulting coordination contracts from Chapter 6 may lead to equilibrium situations between the participating providers and clients. The characteristic of this equilibrium is analyzed in the last chapter (Chapter 7), where the SBDN results are compared with results obtained from the integrated Game Theory (GT) method.

In Chapter 7, a novel integrated GT method is proposed for the inter-organizational coordination under uncertain and competitive circumstances. The competences between the providers/clients are captured through Nash Equilibrium (NE) games. The contrasting objectives between the main game players (provider and client, participating as full production SCs) are modeled through a non-cooperative non-zero-sum non-symmetric roles Stackelberg-game under the leading role of the client. This concept is similar to the SBDN concept, however, the difference is in the methodology. In the SBDN, the leader designs the coordination contract by offering the transfer price and the quantities along time (see Chapter 6). While, the Stackelberg game is based on sharing the preparation of the coordination contract: the leader offers the transfer price of the inner component (conflicting resource), and the follower player offers the quantities over the planning time horizon. The SBDN methodology proposed in Chapter 6) considers the uncertainty of the follower partner as a way to help the leader partner to anticipate the follower response when designing the coordination agreement, and to help the follower partner to evaluate the coordination agreement offered by the leader partner.

The problem statement of Chapter 6 is extended to consider the uncertain behavior of all participants resulting from the uncertain conditions of all third parties. Furthermore, a generic global model is developed considering the full SCs of the external providers/clients (NE- game players) as part of the system, while the external suppliers/customers are considered as third parties, in which they participate with their price policies as in Chapter 5. By this, the holistic global coordinated model proposed in this chapter covers all the issues tackled in the aforementioned chapters, and extends them to globally cope with all possible future enterprises SCs under all possible disruptions.

The integrated GT approach is based on building and evaluating the Stackelberg (expected) payoff matrix under different uncertain situations with the help of the Monte-Carlo sampling method. A set of optimal coordination contracts are built and represented as a novel Stackelberg set of Pareto frontiers. The proposed integrated GT approach helps SCs enterprises stakeholders to identify and manage coordination contracts able to mitigate any possible disruptions, while keeping expected individual profits improvements, in comparison with the standalone case. For the presented case study, the results show that effective coordination/collaboration contracts lead to reductions in the uncertainty effects, represented by the variance of the profit scenarios, that each game player may face due to the dynamic market, and thus stressing their willingness to collaborate.

The game players roles have been switched to study their effect on the game outcome. The results on the presented case study show that, the traditional myth of leading the game does not guarantee higher payoffs, although it affects the game outcome. The game player role as follower rather than as leader results in higher payoffs. The game revenues depend not only on the game players roles, but also on the reaction function, which marks the difference.

The results of the integrated GT approach are compared with the SBDN approach proposed in Chapter 6 considering the uncertain behavior of the follower game player using the same case study. The integrated GT approach leads to better follower expected payoffs than the SBDN approach, while the SBDN leads to better profits for the leader partner. This difference is due to the different methodologies. Unlike the SBDN, the contract energy amounts of the coordination contracts resulting from the integrated GT approach are the optimal amounts that the follower decides according to her/his best conditions, and that explains why the integrated GT approach is more profitable for the follower player. On the other side, using the SBDN, the leader decides the contract energy amounts according to her/his best conditions considering the probability of acceptance of the follower. This explains why the SBDN is more profitable for the leader partner.

In summary, this thesis adds to the PSE and OR communities several decision-support tools that are practical and generic enough to be applied to different situations (standalone, centralized, and decentralized) allowing all participants to share responsibilities and risks under different competitive and uncertain circumstances. This thesis proves that the performance of the SC decentralized system depends on the actions and the role of each participant.

This thesis covers all the research objectives illustrated in 2.7. Many future research works can be emerged from this document to open the door for new researchers.

8.2 Future research work

This thesis opens a wide range of opportunities for future research in the line of multi enterprise-wide coordination (M-EWC).

- Further research is needed to consider the competence between different leaders/followers, and tools to implement it in real cases. The quality of the data sharing is to be more investigated and integrated into the decentralized modeling system.
- Further research is needed to consider the environmental and social issues in the decentralized-decision making process. This leads to develop new solution techniques able to solve the problem while managing large number of objective functions.
- New sources of uncertainty are to be incorporated such as the resources availability, market trends, product quality, operational uncertainty, capacities, competitive behavior, uncertainty of social issues, environmental measures, etc.
- Combining preventive with reactive approaches when tackling uncertainty based on reliability measures is one of the current challenges to be investigated.
- New methods are to be developed to address the risk-sharing among the collaborating partners.
- The use of grid computing methods based on decomposition techniques is a new interesting topic, in which it can be applied to solve more complex SC models with less computational efforts.
- New combined techniques to tackle uncertainty are to be investigated, such as multi-parametric programming and stochastic programming, and to study how this combination affects the M-EWC decision-making.
- More research efforts are required to use complementarity programs for decentralized SC decision-making modeling.

Appendixes

Appendix A

Publications

This is a list of the publications resulted from the works carried out so far within the scope of this thesis.

A.1 Journals

A.1.1 Manuscripts published

Zamarripa, M.; Hjaila, K.; Silvente, J.; Espuña, A. Tactical Management for Coordinated Multi-echelons Supply Chains. *Computers & Chemical Engineering*, 66: 110-123 **(2014)**.

doi:10.1016/j.compchemeng.2014.02.006.

Hjaila, K.; Laínez-Aguirre, J.M., Puigjaner, L.; Espuña, A. Decentralized Manufacturing Supply Chains Coordination under Uncertain Competitiveness. *Procedia Engineering*, 132: 942-949 **(2015)**. doi:10.1016/j.proeng.2015.12.581.

Hjaila, K.; Laínez-Aguirre, J.M.; Zamarripa, M.; Puigjaner, L.; Espuña, A. Optimal integration of third-parties in a coordinated supply chain management environment. *Computers & Chemical Engineering*, 86: 48-61 **(2016)**. doi:10.1016/j.compchemeng.2015.12.002

Hjaila, K.; Laínez-Aguirre, J.M.; Puigjaner, L.; Espuña, A. Scenario-based dynamic negotiation for the coordination of multi-enterprise supply chains under uncertainty. *Computers & Chemical Engineering*, **(2016)**. In press doi:10.1016/j.compchemeng.2016.04.004.

A.1.2 Manuscripts Accepted

Hjaila, K.; Puigjaner, L.; Espuña, A. Supply Chains Multi-Enterprise-Wide Coordination/Collaboration under Uncertain Competitive Environment. *Computers & Chemical Engineering* **(2016)**. Accepted with comments.

A.2 Conference proceeding articles

Zamarripa, M.; Hjaila, K.; Silvente, J.; Espuña, A. Simplified model for integrated Supply Chains Planning. *Computer Aided Chemical Engineering*, 32:547-552 **(2013)**. doi:10.1016/B978-0-444-63234-0.50092-0.

Zamarripa, M.; Hjaila, K.; Cóccola, M.; Silvente, J.; Méndez, C.; Espuña, A. Knowledge-based approach for the integration of the planning and scheduling decision making levels. *Chem. Eng. Trans*, 32:1339-1344 **(2013)**. . doi:10.3303/CET1332224

Hjaila, K.; Zamarripa, M.; Shokry, A; Espuña, A. Application of pricing policies for coordinated management of supply chains. *Computer Aided Chemical Engineering*, 33:475-480 **(2014)**.doi:10.1016/B978-0-444-63456-6.50080-6.

Hjaila, K.; Puigjaner, L.; Espuña, A. Scenario-based price negotiations vs. game theory in the optimization of coordinated supply chains. *Computer Aided Chemical Engineering*, 37:1859-1864 **2015**. doi:10.1016/B978-0-444-63576-1.50004-2.

Hjaila, K.; Laínez-Aguirre, J.M.; Puigjaner, L.; Espuña, A. Management coordination for superstructures of decentralized supply chains under uncertainty. *Operations Research Proceedings 2015* **(2015)**.

A.3 Other congresses and workshops

Zamarripa, M.; Hjaila, K.; Silvente, J.; Espuña, A. Simplified model for integrated Supply Chains Planning. *23rd European Symposium on Computer Aided Process Engineering (ESCAPE-23)*, 9-12 June 2013, Lappeenranta, Finland. *Oral presentation.*

Zamarripa, M.; Cóccola, M.; Hjaila, K.; Silvente, J.; Méndez, C.; Espuña, A. Knowledge-based approach for the integration of the planning and scheduling decision making levels. *11th International Conference on Chemical & Process Engineering (ICheaP-11)*, 2-5 June 2013- Milan, Italy. *Poster presentation.*

Hjaila, K.; Zamarripa, M.; Shokry, A; Espuña, A. Application of pricing policies for coordinated management of supply chains. *24th European Symposium on Computer Aided Process Engineering (ESCAPE-24)*, 15-18 June 2014- Budapest, Hungary. *Oral presentation.*

Hjaila, K.; Zamarripa, M.; Espuña, A. Analysis of the role of price negotiations and uncertainty in the optimization of coordinated supply chains. *20th Conference of the International Federation of Operational Research Societies (IFORS-20)*, 13-18 July 2014 - Barcelona, Spain. *Oral presentation.*

Shokry, A.; Hjaila, K.; Espuña, A. Adaptative evolutionary optimization of complex processes using a kriging based genetic algorithm. *The 13th Mediterranean Congress of Chemical Engineering (MCCE13)*, 30 Sep-3 Oct 2014- Barcelona, Spain. *Oral presentation.*

Hjaila, K.; Puigjaner, L.; Espuña, A. Negotiations Provider-Client for Supply Chains Coordination under Competitiveness. *Computer Aided Process Engineering (CAPE-Forum 2015)*, 27-29 April 2015- Paderborn, Germany. *Oral presentation.*

Hjaila, K.; Puigjaner, L.; Espuña, A. Scenario-based price negotiations vs. game theory in the optimization of coordinated supply chains. *12th conference of PSE and 25th European Symposium on Computer Aided Process Engineering (PSE2015/ESCAPE25)*, 31 May-4 June 2015, Copenhagen - Denmark. *Poster presentation.*

Hjaila, K.; Laínez-Aguirre, J.M.; Puigjaner, L.; Espuña, A. Non-cooperative games for the optimization of multi-enterprise supply chains under uncertainty. *AIChE Annual Meeting-2015*, 8-13 November 2015, Salt Lake City, US. *Oral presentation.*

Hjaila, K.; Laínez-Aguirre, J.M.; Puigjaner, L.; Espuña, A. Application of game theory to the optimization of decentralized supply chains under uncertainty. *10th European Congress of Chemical Engineering (ECCE10)*, 7 Sep- 01 Oct 2015 - Nice, France. *Keynote presentation.*

Hjaila, K.; Laínez-Aguirre, J.M.; Puigjaner, L.; Espuña, A. Game-based modeling for the optimal management of decentralized supply chains under competitiveness. *27th European Conference on Operational Research (EURO27)*, 12 - 15 July 2015, Glasgow, UK. *Oral presentation.*

Hjaila, K.; Puigjaner, L.; Espuña, A. Tactical Management of Decentralized Supply Chains Superstructures under Uncertainty. *27th European Conference on Operational Research (EURO27)*, 12 - 15 July 2015, Glasgow, UK. *Poster presentation.*

Hjaila, K.; Puigjaner, L.; Espuña, A. Decentralized Manufacturing Supply Chains Coordination under Uncertain Competitiveness. *The Manufacturing Engineering Society International Conference (MESIC 2015)*, 22-24 July 2015, Barcelona, Spain. *Poster presentation.*

Hjaila, K.; Laínez-Aguirre, J.M.; Puigjaner, L.; Espuña, A. Management Coordination for Superstructures of Decentralized Large Scale Supply Chains under Uncertainty. *International Conference on Operations Research (OR2015)*, 1-4 September 2015. Vienna, Austria. *Invited oral presentation.*

Hjaila, K.; Puigjaner, L.; Espuña, A. Optimal Strategic and Tactical Decision-Making of Decentralized Multi-Enterprise Multi-Period Supply Chains under Uncertainty. *AIChE Annual Meeting-2016*, 13-18 November 2016. San Francisco- US.

A.4 Awards

- The scholarship of "Agència de Gestió d'Ajuts Universitaris i de Recerca AGAUR".
- One of the best PSE SC themes in the PSE2015/ESCAPE25 conference. For more information see `http://www.pse2015escape25.dk/` and `https://www.youtube.com/watch?v=ZhfArdSjGtY`.
- One of the PSE SC papers of special interest in the PSE2015/ESCAPE25 conference. For more information see `http://www.pse2015escape25.dk/` and `https://www.youtube.com/watch?v=ZhfArdSjGtY`.

Appendix B

Case Study Data

This appendix presents the case study data used along the thesis (Tables B.1-B.11).

Table B.1: Energy generation parameters

RM	price (m.u./kg)	Generation cost (m.u./kWh)		Generation ratio (m.u./kWh)	
		g1-g3	g4-g6	g1-g3	g4-g6
b1 (Wood pellets)	0.070	0.26	0.13	0.73	1.50
b2 (Coal)	0.045	0.20	0.14	2.00	2.60
b3 (Petcoke)	0.075	0.21	0.15	0.85	1.80
b4 (Marc waste)	0.065	0.23	0.135	0.80	2.00

Table B.2: Distance between RM supplier and energy generation plants

Supplier	Distance to energy plants (km)					
	g1	g2	g3	g4	g5	g6
s1	180	150	200	180	150	200

Table B.3: Polystyrene market demands

Products	Markets	Demand (tons)									
		Time periods									
		t1	t2	t3	t4	t5	t6	t7	t8	t9	t10
A	mk1	77.4	72.0	108.0	144.0	72.0	90.0	77.4	63.0	126.0	72.0
	mk2	77.4	72.0	108.0	144.0	72.0	90.0	77.4	63.0	126.0	72.0
	mk3	77.4	72.0	108.0	144.0	72.0	90.0	77.4	63.0	126.0	72.0
B	mk1	77.4	72.0	108.0	144.0	72.0	90.0	77.4	63.0	126.0	72.0
	mk2	77.4	72.0	108.0	144.0	72.0	90.0	77.4	63.0	126.0	72.0
	mk3	77.4	72.0	108.0	144.0	72.0	90.0	77.4	63.0	126.0	72.0

Table B.4: Polystyrene maximum storage capacity

Distribution center	Polystyrene product	Max. storage capacity (tons/period)
dc1	A	500
	B	500
dc2	A	400
	B	400

Table B.5: Polystyrene maximum production capacity

Production plant	Polystyrene product	Max. production capacity (kg/day)
pl1	A	6,500
	B	7,500
pl2	A	8,000
	B	9,000
pl3	A	3,000
	B	4,000

Table B.6: Polystyrene unitary production cost and energy requirement

Polystyrene product	RM	Production cost (m.u./kg)	Energy required (kWh/kg)
A	rm1	0.64	7.33
	rm2	0.62	7.33
B	rm3	0.56	6.98
	rm4	0.53	6.98

Table B.7: Polystyrene RM supply capacity and prices

RM	Price (m.u./kg)	Max. capacity (kg/day)
rm1	1.15	15,000
rm2	1.00	10,000
rm3	1.00	10,000
rm4	1.00	8,000

Table B.8: Distance between polystyrene distribution centers and markets

DC	Distance to markets (km)		
	mk1	mk2	mk3
dc1	100	140	120
dc2	120	150	175

Table B.9: Distance between polystyrene production plants and distribution centers

Production plant	Distance to DC (km)	
	dc1	dc2
pl1	160	120
pl2	150	130
pl3	120	150

Table B.10: Distance between RM suppliers and polystyrene production plants

Supplier	Distance to PL (km)		
	pl1	pl2	pl3
sup1	100	150	145
sup2	200	120	130
sup3	110	70	80
sup4	170	220	215

Table B.11: Energy markets demands

Energy markets	Demand (kWh)	
	Time period	
	t1-t4	t5-t10
me1	300	5000
me2	200	600

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