2014

# The impact of supply chain structures on performance

03/December/2014

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## ACKNOWLEDGEMENT

First of all I want to express my sincere gratitude to my supervisor Prof. Jose M. Framiñán, who gave me the opportunity of research in the exciting field of the Supply Chain Management. He introduced me in a very interesting modeling paradigm that has been demonstrated to be very useful in this field. His insightful advices and continuous and valuable reviews of my work have been very precious for me.

A warm gratitude goes to my co-supervisor Salvatore Cannella, who I met in a research stay in Lisbon. Since the beginning he shared with me his enthusiasm for research, and we started a good collaboration. Even he was very time researching in other centres, his availability, dedication, support and motivation, have been very important for me during my PhD.

A special thank is for my family, who supported me during my academic life, since the beginning of my bachelor degree until the end of this PhD.

Very special thanks go to Beatriz, who has built it up with me during the last year of my PhD. Her empathy, patience, optimism, understanding, and her constant support have been more important for me than she actually believes.

Finally, to those members of the DOIGE I who shared with me very valuable knowledge, advices, and coffees during this period, thank you.


Sincerely,


Roberto Domínguez

Sevilla, December 2013

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# PART I

Introduction

# Chapter 1: Introduction

## 1.1 CONTEXT AND PROBLEM STATEMENT

A Supply Chain Network (SCN) can be defined as a network of autonomous or semiautonomous business entities collectively responsible for procurement, manufacturing and distribution activities associated with one or more families of related products (Swaminathan *et al*., 1998). Since the 1980s, there has been tremendous interest for both researchers and practitioners in the area of Supply Chain Management (SCM), due to the increasing importance of designing and maintaining lean, agile, flexible and efficient SCNs. SCM may be viewed as an integrated approach to increasing the effectiveness of the SCN through improved coordinated efforts between the upstream and downstream organizations in the system (Hwarng *et al*., 2005). SCM has to deal with increasingly complex SCNs due to rapid technological advances, the increase of customer expectation, the enlargement and geographically diverse sourcing arrangements as well as the globalization of trade (Modrak *et al*., 2012). As manufacturing practice shifts toward the outsourcing paradigm, the SCM takes place throughout a high number of entities, generating a highly interdependence between them and making SCM a complex process and demanding a high coordination between partners. This coordination is rarely found (enterprises are not willing to share private information) and it has been recognized as a root cause of one of the most devastating phenomenon in SCM: the bullwhip effect (BWE) (Bhattacharya and Bandyopadhyay, 2011).

BWE refers to a progressive increase in order (demand) variance as order information passes upstream in a SCN, from the customer back to the supplier level. Essentially, orders placed by upstream SCN nodes show increased variability, i.e. variance amplification (Chatfield and Pritchard, 2013; Strozzi *et al*., 2012). This is known to inevitably lead to excessive inventory investment, poor customer service, lost revenues, misguided capacity plans, ineffective transportation, and missed production schedules (Chen *et al*. 2012). As a consequence, this effect increases the cost of operating the SCN, producing inefficiencies that lets costs increasing up to 25 per cent, deteriorating profitability of 15-30 per cent, increasing annual inventory holding costs

of 33 per cent, and cost of capital of 13 per cent (Turrisi *et al.*, 2013). Nowadays, about two-thirds of firms are affected by the BWE (see e.g. Shan *et al.*, 2013; Bray and Mendelson, 2012). Thus, BWE is one of the most widely investigated phenomena in the modern day SCN management research (Nepal *et al.*, 2012; Zotteri, 2013).

In order to analyze the BWE under real business world conditions, increasingly complex mathematical representations of SCNs (such as multi-product scenarios, stochastic lead times, production/distribution capacity constraints, reverse logistic and so on) have been developed. However, several assumptions are commonly made to simplify the analysis (Chatfield, 2013), being one of the most relevant what it can be labeled as a "serial structure model", i.e. each echelon in the system has a single successor and a single predecessor. Undoubtedly, the serial SCN system analysis represents a powerful technique for studying the dynamics of the BWE, but this assumption is seldom verified in real SCNs (Bhattacharya and Bandyopadhyay, 2011). Essentially, due to the complexity and mathematical intractability of multi-echelon systems, most of the scientific works dealing with the study of the BWE are confined to the classical single-echelon, dyadic or the serially-linked structure (Sucky, 2009; Bhattacharya and Bandyopadhyay, 2011; Giard and Sali, 2013).

However, modern SCNs, due to the globalization of trade and the outsourcing paradigm are characterized by a high multiplicity (high number of elements and interactions), often presenting configurations that differ from the simplistic serially-linked or dyadic topologies (characterized by a low multiplicity). Hence, the research on SCNs should use complex SCN models that allow modeling modern SCN configurations in order to obtain results as closer as possible to the dynamics of real SCNs. In other words, there is a need of modeling other SCN configurations found in real business enterprises such as convergent, divergent or conjoined (Strader *et al.*, 1998; Lin and Shaw, 1998; Beamon and Chen, 2001; Giard and Sali, 2013).

Convergent SCNs are assembly-types configurations in which a wide range of materials and subcomponents provided by suppliers converges through a series of manufacturing stages until the final product is assembled at one location. Automobile and aerospace industries are associated with this configuration. On the contrary, divergent SCNs are distribution-like configurations, in which a relatively small number of suppliers provide materials and subcomponents that are used to produce a number of generic product models. Appliances, electronics, and computer industries can be

classified as divergent SCNs. Finally, the conjoined configuration is a combination of the convergent and divergent configurations: first a convergent phase where finished products are manufactured, and a second phase for distributing the finished products. Since distribution phase is present in most of SCNs, this Thesis is focused on the divergent configuration.

Modeling such SCNs by classic methods presents many problems since SCNs are representative *Complex Adaptive Systems* (CAS) (Chen, 2012; Li *et al*., 2010a,b; Bozarth *et al*., 2009; Wang *et al*., 2008; Pathak *et al*., 2007; Sun and Wu, 2005; Surana *et al*., 2005; Choi *et al*., 2001). A CAS is a dynamic network where many agents act simultaneously and continuously react to the actions of the other agents. These systems are characterized by a non-predetermined order (emergent order), an irreversible system history, and an unpredictable future (Mitchell, 1994). Moreover, as Bonabeau (2002) claims, the only way to analyze and understand emergent phenomena is to model the system from the bottom up.

In order to cope with this complexity, simulation is often selected as one of the best solutions to model SCNs (Yoo and Glardon, 2009). A simulation framework that is able to both view a complex SCN and examine various causes and their effects at the same time, would provide new insight to the various forces and dynamics in a SCN (Alony and Munoz, 2007). In this regard, a modeling and simulation approach influenced by the complexity paradigm is MAS (Multi-Agent System), derived partly from object-oriented programming and distributed artificial intelligence, and partly from insights from the science of complexity. A MAS is an adequate approach for modeling CAS and it is useful in creating understandable results for managers (Nilsson and Darley, 2006).

## 1.2. RESEARCH OBJECTIVES AND OUTLINE OF THE THESIS

The research objectives of this Thesis are:

i. Developing a simulation software tool for modeling and simulating complex SCNs configurations (Part I). The simulation tool takes the name of the project by which this Thesis has been funded: SCOPE (*Sistemas COoperativos para la Programación y Ejecución de pedidos*).

ii. Analyzing and determining the impact of the structure of SCNs on the BWE (Part II).

The Thesis is organized in four parts. Part I introduces the context, problem statement and the main objectives of the Thesis (present Chapter 1). Then, Chapter 2 provides a description of SCNs and SCM, along with a literature review on BWE. Part II describes the first objective of the Thesis. It is structured in three chapters: Chapter 3 is a literature review of MAS applications, modeling frameworks, and simulation platforms on SCM problems; Chapter 4 describes the design of a MAS-based framework for modeling complex SCNs; and Chapter 5 describes the implementation of the framework on a MAS software platform (Swarm) and its validation. Part III describes the second objective of the Thesis. It is structured in three chapters as well: Chapter 6 is a comparison analysis of the BWE between a divergent SCN and a serial SCN; Chapter 7 is a comparison analysis of two BWE avoiding strategies (information sharing and smoothing order-up-to policies) between a divergent SCN and a serial SCN; in Chapter 8 a structured design of experiments is performed, by which the divergent SCN configuration is exhaustively varied according to its structural factors, in order to identify a relation between the structure of the network and the BWE. Finally, Part IV is the conclusions of the Thesis (Chapter 9).

# Chapter 2: Supply Chain Networks and Bullwhip Effect

## 2.1. INTRODUCTION

This is an introductory chapter on SCNs and BWE. First, SCN and SCM are defined, describing why SCNs are considered complex systems and highlighting the problems faced by researchers in order to model the SCN system. Then, it follows a literature review on BWE, introducing the phenomenon and its main causes, and identifying the research gaps related to the structure of the SCNs, which is the focus of this Thesis. Next, a framework for BWE analysis proposed by Towill *et al.* (2007), which is extensively used in the last chapters of the Thesis, is shortly introduced. After that, a collection of metrics for measuring the BWE are described. Finally, a SCN reference model (SCOR) used as reference in the design of SCOPE (see Chapter 4) is briefly introduced.

## 2.2. SUPPLY CHAIN NETWORKS

A SCN is referred to as a complex network of organizations that synchronizes a series of inter-related business processes, such as procurement, manufacturing and distribution, to create values to final customers in the form of one or more families of related products or services (Li *et al.*, 2009). SCM involves the systemic and strategic coordination of products/services, finances and information flows within and across companies in the SCN with the aim of reducing costs, improving customer satisfaction and gaining competitive advantage for both independent companies and the SCN as a whole (Serdarasan, 2013). It involves complex interactions among suppliers, manufacturers, distributors, third-party logistics providers, retailers, and customers. These entities operate subject to different sets of constraints and objectives. However, they are highly interdependent when it comes to improving performance of the SCN. As a result, decision of any entity in a SCN depends on the performance of others, and their willingness and ability to coordinate activities within the SCN (Wen *et al.*, 2012). The numerous interactions between entities as well as the characteristics of nonlinearity,

dynamics etc. in SCNs make it challenging to analyze and predict their responses over time.

So far, considerable endeavors have been made to construct models and predict their performance. The conventional models of SCNs in the literatures mainly focus on the issue from the three levels: strategic level, which includes location/allocation decisions, demand planning, distribution channel planning etc; tactical level, which covers inventory control, production distribution coordination, order/freight consolidation etc. and operational level, vehicle routing/scheduling, workforce scheduling, record keeping, and packaging belong to this level (Li *et al.*, 2010a). These previous researches provide a beneficial insight on SCNs and they address problems mainly from the microscopic view i.e., focusing on either the focal entity or relations between two entities in the SCNs. However, there are few literatures to describe and analyze the whole performance of the SCN (Wen *et al.*, 2012). How to establish the whole model of the SCN and analysis its characteristics is a challenge of research.

SCNs have often been conceptualized as simple linear systems represented by an event dependent series of firms interacting through dyadic relationships (Cox *et al.*, 2006). However, this linear conception of sequential dyadic relationships, while appealing, grossly oversimplifies and distorts the realities of modern SCNs (Hearnshaw and Wilson, 2013), such as those mentioned in Butner (2010), Christopher and Holweg (2011) and Stank *et al.* (2011), and fails to adequately account for the interdependence between a large number of heterogeneous firms present in SCNs (Choi *et al.*, 2001; Kim *et al.*, 2011). Nowadays, the current tendency to features more tailored to customers' individual needs–wider product variety, smaller production lot sizes, more echelons and different actors to co-ordinate within each SCN, etc.–(Perona and Miragliotta, 2004), the increase of customer expectation, the enlargement of outsourcing as well as the globalization of trade have led to SCNs much complicated. Most researchers come to realize that SCNs are representative complex systems (Bozarth *et al.*, 2009; Li *et al.*, 2010a; Zhu and Xu, 2012; Modrak *et al.*, 2012; Serdarasan, 2013), in which a large number of firms operate simultaneously with many supply partners and interact through a variety of information and material flows in an uncertain way (Sivadasan *et al.*, 2006). Furthermore, its overall behavior cannot be described exhaustive, although there is comprehensive knowledge of its components and their interaction (Pratt *et al.* 2005). These characteristics of complex systems are particularly well modeled by modern

modeling approaches such as MAS (see Chapter 3). Summarizing, the complexity of SCNs requires SCNs to be analyzed on the network level, which adds more interrelations, dynamics, and complexity as compared to the more basic and linear chain level (Moser *et al.*, 2011, Xuan *et al.*, 2011; Ma *et al.*, 2013).

In order to manage such complex systems and respond appropriately to exigencies, SCNs managers are required to have an understanding of the underlying structure of their system and how their firms interact (Hearnshaw and Wilson, 2013). Indeed, Choi and Hong (2002) acknowledge that if we are to truly practice the management of SCNs, we need to understand the structure of SCNs.

## 2.3. BULLWHIP EFFECT

### 2.3.1. Introduction

The BWE is one of the most widely investigated phenomena in the modern day SCN management research (Nepal *et al.*, 2012), since it has been recognized as one of the main obstacles for improving SCN performance. In the presence of this phenomenon, orders placed by upstream nodes exhibit a higher variability as compared to that of orders placed by their downstream partners (Chatfield and Pritchard, 2013), having many undesirable effects such as increasing stock and generating stock-outs (Adenso-Diaz *et al.*, 2012). The BWE is relevant both for individual companies that face an unnecessarily variable demand as well as for the entire SCN (Zotteri, 2012). Moreover, the most recent economic downturn has no doubt created a lot of bullwhips around the world (Lee, 2010). For instance, the electronics manufacturing sector has experienced something akin to the BWE in terms of larger sales declines occurring further upstream (Dvorak, 2009). More specifically, in the last quarter of 2008, consumer demand had declined 8 percent, while product shipments fell 10 percent and chip sales fell 20 percent. These data suggest that electronics retailers, wholesalers and manufacturers responded differently to the decline in consumer demand (Dooley *et al.*, 2010).

The investigation on this phenomenon has passed through diverse phases, from empirical and *ad hoc* studies on BWE causes to mathematical approaches to infer on demand amplification solutions. Bullwhip Avoidance Phase is the term coined by Holweg and Disney (2005) to identify the current phase of the studies devoted to the

demand amplification phenomenon. One distinctive feature of this phase is the focus on the efficacy of BWE solving approaches (Cannella and Ciancimino, 2010). To accomplish this aim, increasingly complex mathematical representations of SCNs have been developed to analyze solving approaches under several scenarios, characterized by reverse logistic, multi-product scenarios, different forecasting techniques, stochastic lead times, collaborative systems, capacity constraints, batching, parameter configuration, pricing and so on.

### 2.3.2. Causes

Among the streams of research dealing with BWE, an important one has focused on demonstrating its existence and on identifying its possible causes (Sucky, 2009), and different root causes have been identified. Lee *et al*. (1997) provided the seminal work that defined the BWE and identified the well-known five causes (Disney and Lambrecht, 2008; Zotteri, 2012). A further relevant framework was proposed by Geary *et al*. (2006). The authors identified 10 published causes of BWE, based on the works of Mitchell (1924), Wikner *et al*. (1992), and Lee *et al*. (1997).

Recently Bhattacharya and Bandyopadhyay (2011) identifies 19 causes, 16 operational and 3 behavioral. Operational causes include demand forecasting (Syntetos *et al*., 2009; Trapero *et al*., 2012), order batching (Potter and Disney, 2006), price fluctuation (Ma *et al*., 2013; Lu *et al*., 2012), rationing and shortage gaming, lead time, inventory policy, replenishment policy, improper control system (Disney and Towill, 2003; Syntetos *et al*., 2011), lack of transparency (Cannella *et al*., 2011; Hussain *et al*., 2012), number of echelons (Disney *et al*., 2004; Paik and Bagchi, 2007), multiplier effect, lack of synchronization (Ciancimino *et al*., 2012), misperception of feedback (Gonçalvez *et al*., 2005), local optimization without global vision (Disney and Lambrecht, 2008), company processes (Holweg *et al*, 2005) and capacity limits (Cannella *et al*., 2008; Crespo-Marquez, 2010). The behavioral causes cover neglecting time delays in making ordering decisions (Wu and Katok, 2006), lack of learning and/or training (Akkermans and Voss, 2013) and fear of empty stock (Croson and Donohue, 2006).

### 2.3.3. Bullwhip effect and the structure of the SCN

The potential relation between the SCN structure—defined as the arrangement of the various SCN nodes (Giard and Sali, 2013)—and the BWE is almost unknown. The related published works have only explicitly investigated the impact of the number of echelons in the BWE. Probably, this is mainly because, in SCN literature most of the scientific works dealing with the study of the BWE are confined to the classical single-echelon, dyadic or the serially-linked configuration (Disney *et al*., 2004a; Sucky, 2009; Bhattacharya and Bandyopadhyay, 2011; Giard and Sali, 2013). In fact the serially-linked assumption, i.e. each echelon *k* in the system has a single successor *k+1* and a single predecessor *k-1*, is commonly made in order to simplify the analysis of the BWE (Chatfield and Pritchard, 2013).

The number of echelons or 'number of channel intermediaries' (Disney and Lambrecth, 2008) is a root cause of the BWE that explicitly depends on the structure of the SCN. In fact, there is a common agreement on the existence of a positive correlation between the reduction of the intermediate stages in the SCN and the reduction of the BWE (Disney *et al*., 2004; Paik and Bagchi, 2007; Disney and Lambrecth, 2008; Bottani and Montanari, 2010; Yang *et al*., 2011; Sodhi and Tang, 2011). However, the number of echelons only represents an indicator of the structure of the SCN.

Rarely the BWE has been investigated in more complex configurations (Sucky, 2009), assuming that the SCN structure has an influence on the BWE phenomena (Giard and Sali, 2013). There are only a few anecdotic evidences on the relation between key structural factors of SCNs and the BWE which, still, do not provide information on the impact of the different factors in the BWE (see e.g. Sodhi and Tang, 2011).

Table 2.1 reports an overview of relevant contributions published during the Bullwhip Avoidance Phase. Articles are classified according to the focus on the parameters and factors investigated (e.g., information sharing, lead time, order policy and demand forecasting), and the typology of SCN structure (e.g. serial and non-serial).

All aforementioned papers have largely contributed to better understand the causes, economics consequences and remedies to BWE. Regardless the adopted methodological approaches, the modeled SCN structure and the metrics used to evaluate the SCN performance, the results have shown how factors such as lead time, the adoption of

innovative order policy, specific forecasting techniques and different customer demand patterns can impact on the performance of SCN in terms of demand amplification. However, most of the above-reported studies, in order to quantitatively assess the performance of SCN, have exclusively adopted the classical single echelon structure or the two-stage serial SCN (Bhattacharya and Bandyopadhyay, 2011). Even though many researchers have argued that the results obtained for a single-echelon environment should work in a multi-echelon environment, it has been shown recently that this assumption does not necessarily hold (Cattani *et al.*, 2011). In other studies, in order to assess the performance at different level of a multi-echelon system, it has been used the well-know four-echelon "beer-game" (Sterman, 1989) model (i.e. Retailer, Wholesaler, Distributor and Manufacturer). However, even in this case, most of those studies have adopted a classical serial SCN assumption. Essentially, most of the scientific work in SCN dynamics concerns pure retail/distribution chains or serial SCNs with few stages.

It can be appreciated in Table 2.1 that there are only few studies based on the non-serial SCN modeling assumption investigating the dynamics of SCNs and demand amplification phenomenon. However, most of these papers do not report any insight on the different dynamics between the modeled SCN and the classical serial SCN configuration. The work of Sodhi and Tang (2011) is one of the few papers that have reported some insights on the differences between a serial SCN and a no-serial SCN in terms of their dynamic behavior. They report anecdotal evidence of how the BWE increases as the SCN structure becomes more complex in an arborescent SCN due to the increase in the number of echelons, or in the number of successors at each echelon. However, they do not provide any information on the magnitude of this increment.

The first framework that explicitly considers the SCN structure as a root cause of the BWE is Giard and Sali (2013). The authors perform an extended literature review, classifying approximately 50 articles published in major journals. In their work, authors identify 7 root causes, being the "SCN structure" one among them. According to these authors, the only two works that consider the structure as a potential driver of the BWE are the framework of Geary *et al.* (2006) and the simulation study of Wangphanich *et al.* (2010). The framework of the former authors merely identifies the well-known "number of echelon" as a root cause of the BWE. Analogously, the latter authors, in their analysis of a multi-product SCN do not report any insight on how the structure factors can influence the performance of the SCN. In fact, they focus on the dynamic

response of a fixed SCN structure: a 3-echelon divergent SCN under different order policies and information sharing strategies. Thus, authors do not focus on the relation between the structural factors and the BWE.

**Table 2.1.** An overview of relevant contributions on BWE during the Bullwhip Avoidance Phase.

*Section 1*

| Reference | Information sharing | Lead Time | Order Policy | Forecast | Others | Non-Serial | Serial or dyadic |
|---|---|---|---|---|---|---|---|
| Chen et al. (2000) | ■ | | | ■ | | | ■ |
| Cachon and Fisher (2000) | ■ | ■ | | | | ■ | |
| Thonemann (2002) | ■ | | | | | ■ | |
| Dejonckheere et al. (2002) | | | | ■ | | | ■ |
| Disney and Towill (2003a) | | | ■ | ■ | | | ■ |
| Disney and Towill (2003b) | | | ■ | | | | ■ |
| Dejonckheere et al. (2003a) | | | | ■ | | | ■ |
| Dejonckheere et al. (2003b) | | | | | | | |
| Chatfield et al (2004) | ■ | | | | | | ■ |
| Disney et al. (2004a) | ■ | | ■ | ■ | | | ■ |
| Disney et al. (2004b) | | | | | | | |
| Lee et al. (2004a) | | | | ■ | ■ | | |
| Lee et al. (2004b) | | | | ■ | ■ | | |
| Machuca and Barajas (2004) | ■ | | | | | | ■ |
| Shang et al. (2004) | ■ | | | | | | ■ |
| Warburton (2004) | | ■ | | | | | ■ |
| Zhang (2004) | | | ■ | | | | ■ |
| Chandra and Grabis (2005) | | ■ | | ■ | | | |
| Croson and Donohue (2005) | | | | | | | |
| Gonçalves et al. (2005) | | | | | | | |
| Ingalls et al. (2005) | | | | | | | |
| Wang, et al. (2005) | ■ | | | | ■ | | ■ |
| Byrne and Heavey (2006) | ■ | | | | | | ■ |
| Disney et al. (2006) | | | ■ | | | | ■ |
| Geary, et al. (2006) | | | ■ | ■ | ■ | | ■ |
| Hosoda and Disney (2006a) | | | | ■ | | | ■ |
| Hosoda and Disney (2006b) | | | | | | | ■ |
| Kim et al. (2006) | ■ | | ■ | | | | ■ |
| Lalwani (2006) | | | | | | | ■ |

*Section 2*

| Reference | Information sharing | Lead Time | Order Policy | Forecast | Others | Non-Serial | Serial or dyadic |
|---|---|---|---|---|---|---|---|
| Nienhaus et al. (2006) | | | | | ■ | | ■ |
| Ouyang and Daganzo (2006) | | | | ■ | | | ■ |
| Villegas and Smith (2006) | ■ | | ■ | ■ | | ■ | |
| Zhou and Disney (2006) | | | ■ | | | | ■ |
| Boute et al. (2007) | | ■ | | | | | ■ |
| Cachon et al. (2007) | | | | | ■ | | ■ |
| Chen and Disney (2007) | | ■ | ■ | | | | ■ |
| Ouyang (2007) | ■ | | ■ | | | | ■ |
| Disney et al. (2008) | ■ | | ■ | | | | ■ |
| Hosoda et al.(2008) | ■ | | | | | | ■ |
| Jakšič and Rusjan (2008) | | | ■ | ■ | | | ■ |
| Kim and Springer (2008) | | | ■ | | | | ■ |
| Aggelogiannaki et al.(2008) | | | | | | | ■ |
| Bailey and Francis (2008) | ■ | | | | | | ■ |
| Bayraktar et al. (2008) | | | ■ | ■ | | | ■ |
| Caloiero et al. (2008) | | | ■ | ■ | | | ■ |
| Childerhouse, et al. (2008) | | | | | | | ■ |
| Kelepouris et al. (2008) | | | ■ | | | | ■ |
| Wright and Yuan (2008) | | | ■ | ■ | | | ■ |
| Agrawal et al. (2009) | | | ■ | | | | ■ |
| Balan et al. (2009) | | | | ■ | | | ■ |
| Chen and Lee (2009) | ■ | | ■ | | | | ■ |
| Ben-Tal et al. (2009) | | | ■ | | | | ■ |
| Campuzano, et al(2009) | | ■ | ■ | | | | ■ |
| Cheng (2009) | ■ | | ■ | | | | ■ |
| Özelkan and Çakanyildirim (2009) | | | | | ■ | | ■ |
| O'Donnell et al. (2009) | | | | | ■ | | ■ |
| Pereira et al. (2009) | | | | ■ | ■ | | ■ |
| Ryu, et al. (2009) | ■ | | | | | | ■ |

*Section 3*

| Reference | Information sharing | Lead Time | Order Policy | Forecast | Others | Non-Serial | Serial or dyadic |
|---|---|---|---|---|---|---|---|
| Sucky (2009) | | | | | ■ | ■ | |
| Cannella and Ciancimino (2010) | ■ | | ■ | | | | ■ |
| Chaharsooghi and Heydari (2010) | ■ | ■ | | | | | ■ |
| Yuan et al. (2010) | ■ | | | | | | ■ |
| Bottani and Montanari (2010) | | | | ■ | | ■ | |
| Ouyang (2010) | ■ | | | | | | ■ |
| Sari (2010) | | ■ | ■ | | | | ■ |
| Springer and Kim (2010) | | | | | | | ■ |
| Wangphanich, et al. (2010) | | | | | | | ■ |
| Hussain and Drake (2011) | ■ | | ■ | ■ | | ■ | |
| Ali and Boylan (2011) | ■ | | | ■ | | | ■ |
| Dass and Fox (2011) | | | ■ | | | | ■ |
| Barlas and Gunduz (2011) | | | | | | | ■ |
| Cannella et al. (2011) | ■ | | ■ | ■ | | | ■ |
| Yang et al. (2011) | | | | | | | ■ |
| Sodhi and Tang, (2011) | | | ■ | | ■ | ■ | |
| Kristianto et al. (2012) | | | ■ | ■ | ■ | | ■ |
| Adenso-Diaz et al. (2012) | ■ | | | | | | ■ |
| Hussain et al. (2012) | | | ■ | ■ | | | ■ |
| Cannella et al. (2012) | | | ■ | ■ | | | ■ |
| Nepal et al.(2012) | | | | | | | ■ |
| Chen et al. (2012) | ■ | ■ | | | | ■ | |
| Ciancimino et al. (2012) | | | | | | | ■ |
| Su and Geunes (2012) | | ■ | ■ | | | | ■ |
| Chatfield and Pritchard (2013) | ■ | ■ | ■ | | | | ■ |
| Cho and Lee (2013) | ■ | | ■ | ■ | | | ■ |
| Garcia Salcedo et al. (2013) | ■ | | | | | | ■ |
| Li and Liu (2013) | | ■ | ■ | | | ■ | |

The above findings and the need of analyzing more complex SCNs structures (see Section 2.2) stimulates the need of further structured studies on the quantification of BWE in no-serial SCNs (addressed in Chapter 6) and establishing a relation between the structural factors of the SCN and BWE (addressed in Chapter 8).

### 2.3.4. Bullwhip avoidance strategies and the structure of the SCN

One important stream in the BWE research has mainly focused on the dampening techniques to reduce this detrimental phenomenon. Specifically, two different approaches for avoiding and/or limiting the BWE have received attention: collaboration and information sharing in the SCN and the adoption of the smoothing replenishment rules (Cannella and Ciancimino, 2010).

Information sharing is the practice of making strategic and operation information available for other partners of the network (Stadtler, 2009). There is a common agreement that enforcing co-operation between the participants of the SCN is an effective tool to increase SCN performance (Audy *et al.*, 2012; Stanck *et al.*, 2011; Hall and Saygin, 2012). It creates visibility along the network and helps suppliers to plan their replenishment and delivery schedules (Prajogo and Olhager, 2012). Information sharing is regarded as one of the main drivers to improve or even optimize the overall SCN performance (Voigt and Inderfurth, 2012), eradicating variability in SCNs, preventing costly dynamic distortions such as the BWE (Lee, 2010), spreading the operational risk (Cristopher and Holweg, 2011), and in summary, removing or mitigating harmful problems resulting from the BWE (Cho and Lee, 2011).

At the operational level, SCN collaboration concerns with the alignment of decisions amongst SCN partners in their planning and inventory management on the basis of customers' demands. Firms share real-time market demand data for the generation of conjoint forecasting, or even real-time information on inventory levels and in-transit items for centralized replenishment activities. In any case, each member of the SCN is able to generate order patterns based not only on the information at a local level, but also on further data incoming from partners. This visibility allows limiting the classical information distortion of the traditional SCN (Prajogo and Olhager, 2012).

Perhaps the information sharing strategy studied in the literature is the so-called Information Exchange Supply Chain (Holweg *et al.*, 2005). In this collaborative

structure all echelons include the exchanged information on market demand in the order policy. Thus, retailers and suppliers order independently, yet they exchange demand information and action plans in order to align their forecasts for capacity and long-term planning.

Regarding smoothing replenishment rules, these have been designed to avoid the side-effect of the Order-Up-To (OUT) policy, which is the most commonly used order policy in practice (Teunter and Sani, 2009). It is well-known that the classical OUT policy minimizes inventory fluctuations, but may lead to increasing the BWE (Wei *et al.*, 2013). In fact, whatever forecasting method is used (simple exponential smoothing, moving averages or demand signal processing), OUT will always produce a BWE (Dejonckheere *et al.*, 2003a). In contrast, smoothing replenishment rules do not only increase the flexibility for decision-making, but also allow managers to balance the target of inventory costs and production fluctuations (Wei *et al.*, 2013).

A smoothing replenishment rule is a (*S*, *R*) policy in which the entire deficit between the *S* level and the available inventory is not recovered in a review period (Boute *et al.*, 2009). For each review period *R* the quantity *O* is generated to recover only a fraction of the gap between the target on-hand inventory and the current level of on-hand inventory, and a fraction of the gap between the target pipeline inventory and the current level of pipeline inventory (Cannella *et al.*, 2011). As reported by Wang *et al.* (2012a) this ordering policy was found to mimic real-life decisions made by players of the Beer Game, Sterman (1989). The rationale for the smoothing replenishment rule is to limit the tiers' over-reaction/under-reaction to changes in demand (Cannella and Ciancimino, 2010). This policy is able to solve the detrimental consequence of the adoption of the classical OUT, as it is well recognized that this policy may lead to the BWE (Disney and Towill, 2003a; Wei *et al.*, 2013).

A notorious type of these policies is the Inventory and Order Based Production Control System (IOBPCS) family of smoothing replenishment rules (Coyle, 1977; Towill, 1982). In the last decade, several variations of this family have been developed (e.g. Cannella *et al.*, 2011), such as the Automatic Pipeline Variable Inventory and Order Based Production Control System (APVIOBPCS) by Dejonckheere *et al.* (2003a). In this rule, the order is generated by satisfying the expected demand during the risk period and to recover two gaps. The first gap is that between a variable target net stock value and the current level of inventory. The second is the gap between a

variable target pipeline inventory and the current level of pipeline inventory. This variable target level is updated at each review time on the basis of the expected demand during the risk period.

**Table 2.2.** An overview of relevant contributions on BWE avoidance strategies.

| | ORDER POLICY | | SCN COLLABORATION | | SCN STRUCTURES | |
|---|---|---|---|---|---|---|
| | Classical OUT | Smoothing OUT | Traditional | Information sharing | Serial | Non-serial |
| Chen et al. (2000) | √ | | √ | √ | √ | |
| Disney and Towill (2003a) | | √ | √ | | √ | |
| Disney and Towill (2003b) | | √ | √ | √ | √ | |
| Dejonckheere (2003a) | √ | √ | √ | √ | √ | |
| Dejonckheere et al. (2003b) | √ | √ | √ | | √ | |
| Chatfield et al. (2004) | √ | | √ | √ | √ | |
| Disney et al. (2004a) | | √ | √ | √ | √ | |
| Disney et al. (2004b) | | √ | √ | | √ | |
| Machuca and Barajas (2004) | | √ | √ | √ | √ | |
| Shang et al. (2004) | √ | | √ | | √ | |
| Warburton (2004) | | √ | √ | | √ | |
| Byrne and Heavey (2006) | √ | | √ | √ | √ | |
| Disney et al. (2006) | √ | √ | √ | | √ | |
| Hosoda and Disney (2006) | √ | √ | √ | √ | √ | |
| Kim et al. (2006) | √ | | √ | √ | √ | |
| Lalwani (2006) | √ | √ | √ | | √ | |
| Boute et al. (2007) | | √ | √ | | √ | |
| Chen, Disney (2007) | √ | √ | √ | | √ | |
| Disney et al. (2008) | √ | √ | √ | √ | √ | |
| Hosoda et al. (2008) | √ | | | √ | √ | |
| Jakšič and Rusjan (2008) | | √ | √ | | √ | |
| Kim and Springer (2008) | | √ | √ | | √ | |
| Caloiero et al. (2008) | | √ | √ | | √ | |
| Kelepouris et al. (2008) | √ | | √ | √ | √ | |
| Wright and Yuan (2008) | | √ | √ | | √ | |
| Agrawal et al. (2009) | √ | | √ | √ | √ | |
| Chen and Lee (2009) | | √ | √ | √ | √ | |

| | ORDER POLICY | | SCN COLLABORATION | | SCN STRUCTURES | |
|---|---|---|---|---|---|---|
| | Classical OUT | Smoothing OUT | Traditional | Information sharing | Serial | Non-serial |
| Cannella and Ciancimino (2010) | | √ | √ | √ | √ | |
| Yuan et al. (2010) | | √ | √ | √ | √ | |
| Bottani and Montanari (2010) | √ | | | √ | √ | |
| Sari (2010) | √ | | √ | √ | √ | |
| Hussain and Drake (2011) | | √ | | √ | √ | |
| Cho and Lee (2011) | √ | | √ | √ | √ | |
| Barlas and Gunduz (2011) | √ | √ | √ | √ | √ | |
| Cannella et al. (2011) | | √ | √ | √ | √ | |
| Yang et al. (2011) | | √ | √ | √ | √ | |
| Wang et al. (2011) | √ | | √ | √ | | √ |
| Babai et al. (2011) | √ | | | √ | √ | |
| Kristianto et al. (2012) | √ | √ | | √ | √ | |
| Ali et al. (2012) | √ | | √ | √ | √ | |
| Adenso-Diaz et al. (2012) | √ | √ | √ | √ | √ | |
| Chen et al. (2012) | √ | | | √ | | √ |
| Ciancimino et al. (2012) | | √ | | √ | √ | |
| Hosoda and Disney (2012) | √ | | | √ | √ | |
| Wang et al. (2012a) | | √ | √ | | √ | |
| Wang et al. (2012b) | | √ | √ | | √ | |
| Zhang and Wang (2012) | | √ | √ | | √ | |
| Strozzi et al. (2012) | | √ | √ | | √ | |
| Hall and Saygin (2012) | √ | | | √ | √ | √ |
| Trapero et al. (2012) | √ | | | √ | √ | |
| Cannella et al. (2013) | | √ | √ | √ | √ | |
| Wei et al. (2013) | | √ | √ | | √ | |
| Garcia Salcedo et al. (2013) | √ | | √ | √ | √ | |
| Li (2013) | √ | | √ | √ | | √ |

Table 2.2 summarizes the contributions on the impact of information sharing and smoothing replenishment rules in terms of BWE. The contributions are classified according to the adopted order rule (classical OUT policies or smoothing replenishment policies), typology of collaboration between partners (traditional SCN or information sharing SCN), and the typology of SCN structure (e.g. serial and non-serial).

It can be noticed that, although all aforementioned studies attest that there is scientific evidence that the practices of information sharing and smoothing replenishment rules lead to a reduction of the BWE, when quantitatively assessing the efficacy of these BWE avoidance strategies, most of the studies are confined to the classical single-echelon structure or the serially linked SCN. In addition, the few studies based on the non-serial SCN modeling assumption investigating the dynamics of information sharing and demand amplification phenomenon (see e.g. Wang *et al*., 2011; Chen *et al*., 2012; Hall and Saygin, 2012; Li and Liu, 2013) do not report any insight on the different impact of the smoothing replenishment rules and/or the information sharing practice on a classical serial SCN structure and on a divergent SCN structure.

In summary, there is a lack of consistent studies and experimental reports assessing the BWE dampening features of the information sharing and smoothing replenishment rule in no-serial SCNs.

## 2.4. BULLWHIP EFFECT ANALYSIS

Towill *et al*. (2007) indicated that the detection of BWE depends on which "lens" is used, which in turn depends on the background and requirements of various ''players'' within the value stream. In the complex real world the likelihood is that SCNs will generate even greater inconsistency between alternative variance, shock, and filter lens viewpoints. Basically, the proposed framework suggests the typology of endogenous input that can be adopted in BWE analysis in order to study different characteristics of the SCN.

This Thesis, in order to extend and generalize the analysis of the BWE makes use of two of those lenses: the variance lens and the shock lens. The former aims at inferring on the performance of SCNs for a stationary input demand. The latter aims at inferring on the performance of SCNs for an unexpected and intense change in the end customer demand. This latter approach can be viewed as a "crash test" or a "stress test": studying

the system performance under an intense and violent solicitation test to determine the resilience of a given SCN structure (Cannella and Ciancimino, 2010).

## 2.5. METRICS FOR THE BULLWHIP EFFECT ANALYSIS

First proposed by Chen *et al*. (2000), the Order Rate Variance Ratio ($\Phi$) is the most widely used indicator to detect the BWE (Cannella *et al*., 2013), measuring the internal process efficiency and showing the performance of each node in the SCN. It is a demand-independent measure, allowing the comparison between different SCNs. Nevertheless, measuring the internal process efficiency at the individual level (single echelon) is insufficient as it only accounts for the individual performance of each link in the chain separately (Cannella *et al*., 2013). Therefore, a network measure has to be used as a complementary measure of $\Phi$. The Bullwhip Slope (*BwSl*) summarizes all the ratios obtained for each stage in a single measure, allowing a complete comparison between different SCNs at the network level (Ciancimino *et al*., 2012; Cannella *et al*., 2013). The procedure to calculate this metric is to perform a linear regression on the values of $\Phi$ using the echelon position as independent variable (equation 2.2). A high value of the slope means a fast propagation of the BWE through the SCN, while a low value means a smooth propagation. Since *BwSl* is a synthesis of $\Phi$, there are similar costs associated to this metric (procurement, overtime and subcontracting) but at the network level. Below, these two metrics are summarized.

- Order Rate Variance Ratio of a node $i$ ($\Phi_i$): computed as the ratio of the order variance in a generic node ($\sigma_{O_i}^2$, estimated by $s_{O_i}^2$) to the order variance of the end customer demand ($\sigma_d^2$, estimated by $s_d^2$).

$$\Phi_i = \frac{s_{O_i}^2}{s_d^2} \tag{2.1}$$

- *BwSl*: computed as the slope of the linear regression of the $\Phi$ curve.

$$BwSl = \frac{K \sum_{i=1}^{K} p_i \Phi_i - \sum_{i=1}^{K} p_i \sum_{i=1}^{K} \Phi_i}{K \sum_{i=1}^{K} p_i^2 - \left( \sum_{i=1}^{K} p_i \right)^2} \tag{2.2}$$

Being $K$ the total number of echelons and $p_i$ the position of the $i$th echelon.

The above mentioned metrics have been conceptualized for a serial SCN. Since this Thesis focuses on more complex SCNs, particularly in divergent SCNs, the metrics need to be modified in order to be used on such SCNs. The reason is that divergent SCNs contain, in general, more than one node in each stage. In the serial SCN, the parameter required to compute the different metrics on each stage (i.e. the order variance) is taken from the only node in the stage. In the divergent SCN, it is necessary to find an aggregate measure for the whole stage. To obtain this measure, the orders of every node $j$ in stage $i$ ($O_{ij}$) are considered at the same time and added, resulting in an aggregate order pattern for the stage $i$: $AO_i = \sum_{j=1}^{n_i} O_{ij}$, being $n_i$ the number of nodes in the stage $i$. Following the same procedure, the aggregate end customer demand pattern can be obtained as $Ad = \sum_{j=1}^{n_c} O_{Cj}$, being $n_C$ the number of customers. Then, the aggregate variance of each stage ($\sigma^2_{AO_i}, \sigma^2_{Ad}$) can be estimated ($s^2_{AO_i}, s^2_{Ad}$), and $\Phi_i$ is:

$$\Phi_i = \frac{s^2_{AO_i}}{s^2_{Ad}} \tag{2.3}$$

If all the customer demands are assumed to be independent and each node in the SCN places orders independently, the aggregate variance in each stage $i$ is the sum of the variances of orders of each node $j$ in the stage $i$ ($\sigma^2_{O_{ij}}, \sigma^2_{O_{Cj}}$), estimated by ($s^2_{O_{ij}}, s^2_{O_{Cj}}$), and thus, the calculation of $\Phi_i$:

$$\Phi_i = \frac{\sum_{j=1}^{n_i} s^2_{O_{ij}}}{\sum_{j=1}^{n_c} s^2_{O_{Cj}}} \tag{2.4}$$

## 2.3. SUPPLY CHAIN OPERATIONS REFERENCE (SCOR) MODEL

The SCOR model was developed by the Supply Chain Council (SCC, 2006), founded by a group of 70 companies in 1996. It has been developed to describe the business activities associated with all phases of satisfying a customer's demand. The

model itself contains several sections and is organized around the five primary management processes or activities. These activities are divided in two groups: physical activities (Source, Make, Deliver and Return) to manage the physical resources of the enterprise, and planning activities (Plan) to make decisions. These five management processes are represented in Figure 2.1. By describing SCN using these process building blocks, the model can be used to describe simple SCNs as well as very complex enterprise networks using a common set of definitions.
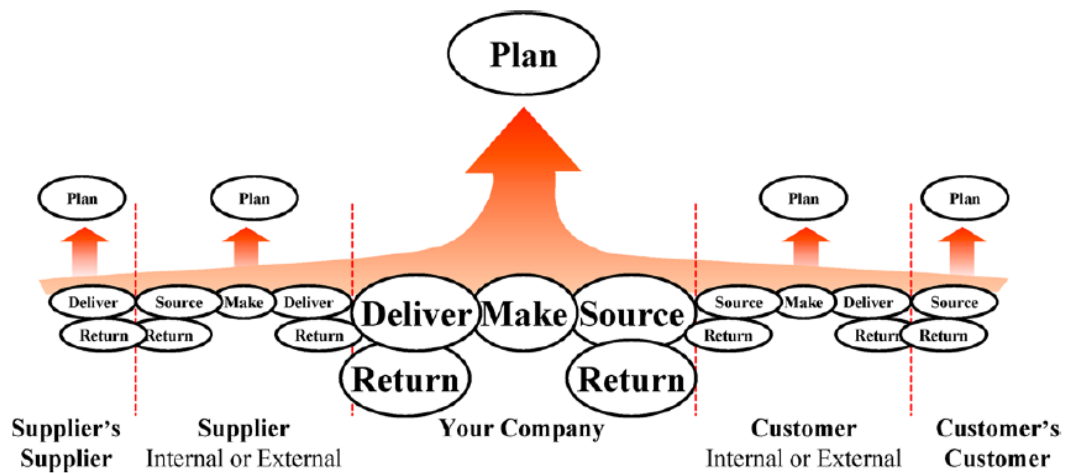


**Figure 2.1.** The five major management processes of SCOR-model (font: Röder and Tibken, 2006).

# PART II

On modeling complex supply chain networks by MAS

# Chapter 3: Literature review on MAS applications on SCM

## 3.1. INTRODUCTION

This chapter introduces the most relevant literature of the last 15 years on the development of models, frameworks and software based on MAS technology, and its application on SCM. Since one of the objectives of the Thesis is the development of a MAS-based framework for modeling and simulating complex SCNs, the literature review has been focused on generic frameworks that allow modeling and simulating a wide variety of SCN configurations (in terms of structure, inventory policies, forecasting, order fulfillment, etc.). However, since there are many others of MAS applications designed to analyze specific problems within the SCM, a general overview of these applications is performed first in order to get an idea of what particular topics have been analyzed by this methodology.

Due to the complexity of SCM, it is very difficult for managers and decision-makers to predict the effects of implementing new management policies and to decide the best strategies to improve the performance of real SCNs. Hence, the existence of SCN modeling tools is very helpful to managers and of great benefit for enterprises. Traditional methods, like analytic models, classical operational research methods, continuous time differential equation models, and discrete time difference equation models are not able to cope with the inherent complexity of SCNs such as the high number of enterprises and interactions between them, or the stochasticity and uncertainty present in most of their processes. Classical operational research methods approaches are not always able to handle the characteristics of dynamic SCNs (Riddals et al., 2001; Long et al., 2011). Analogously, continuous time and discrete time difference equation models are not always suitable for analyzing complex SCN structures, given the high order of differential equations (one tier generally gives a 2nd-4th order system; 2 tiers even 2nd-6th order), which makes analytical analysis difficult (Lee and Kim, 2008; Holweg and Disney, 2005). Thus, new modeling techniques are required.

Simulation has rapidly become a significant methodological approach to theory development in the literature focused on strategy, organizations and SCN management, that allows modelers to capture the dynamics of complex systems like SCNs due to its ease for modeling and its capability of handling their dynamics and stochastic behavior, and enables managers to analyze and evaluate the effects of alternative processes or operation modifications (Chan and Prakash, 2012; Stefanovic *et al*., 2009; Munoz and Clements, 2008; Chatfield *et al*., 2001). Particularly, there is a great interest in modeling SCNs as MAS (Surana et al., 2005; Pathak et al., 2007), because there is a natural correspondence between SCN participants and agents in a simulation model: SCNs tend to be decentralized systems with the participants acting independently, according to their own interests and policies (Long *et al*., 2011). MAS have the capacity to consider the interactions between large numbers of heterogeneous firms allowing SCN managers improving their understanding into how interventions in one part of the SCN may affect another part (Hearnshaw and Wilson, 2013). Thus, the use of MAS turns out to be one of the most effective tools to model and analyze SCNs (Long *et al*., 2011; Chatfield *et al*., 2007).

A key feature of MAS that allows to properly modeling SCNs is the bottom-up methodology by which a MAS model is constructed. This methodology is based on a synthesizing philosophy, where the modeler assumes that he/she cannot understand the whole phenomenon of interest but can observe, on a micro level, specific activities and processes (agents) and tries to understand their behavior. These agents interact and communicate with other agents and they join to form a coherent whole on a macro level, often emerging behaviors that cannot be predicted in advance. On the contrary, top-down methodologies are not able to cope with CAS, since they are based on the assumption that knowledge is outside the system and someone can measure and analyze the observable phenomenon of interest and from that, decompose it correctly into different sub-units, where the sub-problems are solved separately (Nilsson and Darley, 2006). The adoption of MAS has several other benefits: an increasing modeling realism, seeing as individual agents can be made directly comparable to machines, vehicles, products or groups of such, found in a real life context; heterogeneity, because there is no need to aggregate different agents' behavior into average variables; bounded rationality, since the individuals involved lack perfect information, having their own

goals and their own policies; scalability and flexibility, and finally, low cost, since the software needed is open source.

## 3.2. MAS APPLICATIONS IN SCM

A literature review has been performed in order to study the state of the art on MAS applications in SCM. Table 3.1 summarizes the reviewed literature. It can be seen that MAS has been used in the research of a wide variety of topics in SCM in the last decade, such as scheduling, coordination between enterprises, information sharing, order fulfillment process (OFP), collaborative production planning, and provider selection, among others. Further information can be found in Table 3.1, such as their development degree, the role of the agents involved and the software platform used (if any).

The development degree gives an idea of the maturity of works. Three development degrees have been considered:

- Low development degree: presents theoretical models which are not implemented in any software platform and hence, do not provide any results yet.

- Medium development degree: models have been implemented and simulated, providing some coherent results.

- High development degree: models have been implemented in real industry or used to solve a real problem.

Most of the revised literature has a medium development degree, with just a few works with high development degree. From this analysis it is possible to get an idea of the maturity of MAS application in SCM: current research is already developing models and software, but it still needs to give a step through in the development of applications for real industry.

The role of agents determines the granularity (or level of detail) of the models, from low granularity (agents modeling enterprises) to high granularity (agents modeling machines, trucks and other resources). In models with a medium granularity, agents model at a functional level (e.g. departments in each enterprise).

**Table 3.1.** MAS literature review.

| Authors | Topic | Degree of development | Role of agents | Software |
|---|---|---|---|---|
| Abid *et al.* (2004) | Collaborative production planning | High | Functional | Java/Cplex |
| Ahn and Park (2003) | Coordination Information sharing OFP | Medium | Functional | Not described |
| Alpay (2007) | Scheduling | Medium | Resource | Not described |
| Alpay and Saricicek (2008) | Scheduling | Low | Mixed | N/A |
| Álvarez and de la Calle (2009) | Collaborative production planning | Low | Enterprise | N/A |
| Azevedo *et al.* (2004) | OFP | High | Functional | FIPA-OS/Java |
| Bo and Zhiming (2003) | Provider selection Order Management | Medium | Enterprise | Not described |
| Caridi *et al.* (2005) | Collaborative production planning | Medium | Mixed | SIMPLE++ |
| Caridi *et al.* (2006) | Collaborative production planning | Medium | Mixed | SIMPLE++ |
| Chatfield *et al.* (2001,2006,2009) | Framework | Medium | Enterprise | Java/XML/Silk™ |
| Cheeseman *et al.* (2005) | Scheduling | High | Resource | JADE |
| Dong *et al.* (2006) | Framework | Medium | Mixed | Swarm |
| Forget *et al.* (2008) | Multi-Behavior | Low | Enterprise | N/A |
| Forget *et al.* (2009) | Multi-Behavior OFP | Medium | Enterprise | FORAC |
| Framinan (2009) | Order Management | Medium | Enterprise | Swarm |
| Fung and Chen (2005) | Coordination Provider selection | Medium | Functional | Not described |
| Goh and Gan (2005) | OFP | Low | Mixed | N/A |
| Govindu and Chinnam (2010) | Framework | High | Mixed | JADE/Java |
| Guo and Zhang (2009) | Scheduling | Medium | Resource | Not described |
| Hilletofth *et al.* (2009) | OFP | Medium | Mixed | Anylogic |
| Ito and Abadi (2002) | Inventory management | Medium | Mixed | Java |
| Julka *et al.* (2002) | Framework | High | Mixed | Not described |
| Kaihara (2003) | Resource allocation | Medium | Enterprise | Not described |
| Kiralp and Venkatadri (2010) | Framework | Medium | Functional | Not described |
| Komma *et al.* (2011) | Framework | Medium | Resource | JADE |

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**Table 3.1.** MAS literature review (continued).

| Authors | Topic | Degree of development | Role of agents | Software |
|---|---|---|---|---|
| Lin *et al.* (1998) | Information sharing OFP | Medium | Functional | Swarm |
| Lin and Shaw (1998) | Information sharing OFP | Medium | Functional | Swarm |
| Lin *et al.* (2002) | Information sharing Provider selection OFP | Medium | Mixed | Swarm |
| Lin *et al.* (2005) | Provider selection OFP | Medium | Mixed | Swarm |
| Liu and Min (2008) | Collaborative production planning | Low | Mixed | N/A |
| Long *et al.* (2011) | Framework | Medium | Mixed | JADE |
| Nilsson and Darley (2006) | OFP | High | Mixed | Not described |
| Panti *et al.* (2005) | Coordination | Low | Functional | N/A |
| Papadopoulou and Mousavi (2007) | Scheduling | Medium | Resource | JACK |
| Si and Lou (2009) | Inventory management Provider selection Order Management | Medium | Enterprise | Not described |
| Strader *et al.* (1998) | Information sharing OFP | Medium | Functional | Swarm |
| Swaminathan *et al.* (1998) | Framework | Medium | Enterprise | Not described |
| Yoo and Glardon (2009) | Framework | High | Mixed | JADE/Repast |
| Yu and Huang (2001) | OFP | Medium | Functional | Not described |

The role of the agents is chosen depending of the problem to be analyzed. In case of focusing on coordination between enterprises or collaborative planning, agents may play the role of enterprises, while in case of analyzing inventory management policies, order management or OFP, agents may play the functional role. Finally, in the analysis of scheduling problems or resource allocation it might be interesting to choose the resource role for agents. Furthermore, a mixture of roles is possible, allowing the analysis of problems at different levels of details, and increasing the flexibility and realism of models. The literature review reveals that, in fact, mixing different roles of agents is the preferred choice by authors, primarily mixing enterprise and functional roles.

## 3.3. FRAMEWORKS

The above review gives a general overview of the state of the art on the application of MAS to SCM. Now it is time to focus on generic MAS frameworks for SCN modeling. One of the first frameworks that appear in the literature is described in Swaminathan *et al*. (1998). They create a library of re-usable components using agents to model the different enterprises in the SCN and objects to model the control policies for the simulation of material, information and cash flows. Some concepts of this framework were used by IBM to develop a SCN re-engineering tool. Julka *et al*. (2002) model the enterprises using only one generic agent (instead of using one agent per enterprise type), and then create its behavior with customizable internal departments, modeled as sub-agents. This framework was implemented using ADE (Agent Development Environment), and its applicability was shown on a prototype decision support system to study the effects of internal policies, exogenous events, and plant modifications in a petroleum refinery. Dong *et al*. (2006) model the enterprises and their departments as agents, and the material, information and cash flows as objects. They use Swarm to implement the model. Chatfield *et al*. (2001, 2006 and 2009) present SISCO: Simulator for Integrated Supply Chain Operations, for the storage, modeling, and generation of SCN, where the user specifies the structure and policies of a SCN using a Graphical User Interface (GUI) based application, and then saves the SCN description in the open eXtensible Markup Language (XML) based Supply Chain Modeling Language (SCML) format. SISCO automatically generates the simulation model when needed by mapping the contents of the SCML file to a library of supply-chain-oriented simulation classes. Govindu and Chinnam (2010) develop a framework based on SCOR model (SCC, 2006), that allows modeling different segments of the SCN at either aggregated or detailed levels resulting in models of hybrid resolution, facilitating the study of intra- and inter-organizational dynamics. The framework is formed by an extensive library of organizational agents, supply chain agents, behavior and policy objects, and it was implemented in Java, using JADE for agents development. The authors use MASCF (Multi-Agent Supply Chain Framework), a generic methodological framework focusing on the analysis and design phases of development of supply chain applications, described in detail in Govindu and Chinnam (2007). Kiralp and Venkatadri (2010) develop the DSOPP platform (Distributed Simulation of Order Promising Protocols). The framework is built around a scalable

multi-period optimization model that may be used across enterprises. Its goal is to show the feasibility of collaborative decision making and the study of order promising and production planning in the SCN. Long *et al*. (2011) develop a framework with multi-layers for modeling and distributed simulation of complex SCN, using JADE (Java Agent DEvelopment framework). The enterprises are constructed by instantiation of generic agents. The platform supports multi-layered simulation modeling and it is capable to change concept models with different granularities into simulation models.

The design of the framework of SCOPE (described in Chapter 4) takes use of some key features of the above frameworks. These key features are described next and summarized in Table 3.2.

- SCOR model. In the above literature, only Govindu and Chinnam (2010) use a well known model of SCN description (SCOR) to design the structure of the agents in the framework. Since SCOPE aims to precisely capture the internal dynamics of enterprises and SCNs, its basic design is based on the SCOR model.

- Supply Chain Planning Matrix. In order to ensure that all main activities carried out by enterprises are modeled, the mid-term and short-term planning functions described in the Supply Chain Planning Matrix of Stadtler (2005) have been considered in the design of SCOPE. No one of the previous authors has explicitly included all these functions in their agents.

- Detailed manufacturing process. Julka *et al*. (2002) and Long *et al*. (2011) have paid special attention to model with detail the manufacturing process. Manufacturing is a complex task and one of the most important processes in SCM, so it has been modeled with detail in SCOPE, allowing multiple shop floor configurations and manufacturing characteristics.

- Stochastic processes. Many of the processes that take place in SCNs are often stochastic, like the transportation lead time (inter-enterprise) or the machine process time (intra-enterprise). Authors like Chatfield *et al*. (2001, 2006, and 2009) and Long *et al*. (2011) have included some of these uncertainties in their frameworks. SCOPE allows modeling this kind of internal uncertainties.

- Reusability. In Julka *et al*. (2002), authors exploited the reusability of agents and simplified the structure of the framework, with one generic-configurable agent to model each of the enterprises in the SCN, which can be customized with

different functional agents. A similar structure of agents has been adopted in SCOPE.

- Intra-enterprise and inter-enterprise process modeling. The frameworks of Julka *et al*. (2002), Dong *et al*. (2006) and Govindu and Chinnam (2010) are able to model and analyze intra-enterprise and inter-enterprise processes, which is very valuable for SCN analysis since it involves at the same time the departments of each enterprise and all the enterprises in the SCN. Hence, this characteristic has been included in SCOPE.

- External solver. Kiralp and Venkatadri (2010) use an external solver/optimizer for solving linear programming models (like the planning models). SCOPE can be connected as well to an external solver, leaving the task of solving mathematical models to a professional solver and facilitating the addiction of other linear programming models to the agents.

**Table 3.2.** Key features of SCOPE and related literature.

| Author | SCOR | Supply Chain Planning Matrix | Detailed manufacturing process | Stochastic processes | Reusability | Intra/Inter-enterprise modeling | External solver |
|---|---|---|---|---|---|---|---|
| Swaminathan et al. (1998) | | | | | | | |
| Julka et al. (2002) | | | X | | X | X | |
| Dong et al. (2006) | | | | | | X | |
| Chatfield et al. (2001,2006,2009) | | | | X | | | |
| Govindu y Chinnam (2010) | X | | | | | X | |
| Kiralp y Venkatadri (2010) | | | | | | | X |
| Long et al. (2011) | | | X | X | | | |
| **SCOPE** | **X** | **X** | **X** | **X** | **X** | **X** | **X** |

## 3.4. CONCLUSIONS

All the above frameworks/platforms have largely contributed to the literature of SCN modeling with MAS. In the design of the framework of SCOPE, many characteristics of

the previous works have been included. Furthermore, SCOPE is conceived to be open-source and help practitioners in their research: its modular design makes easy to add new functions and behaviors to the agents and hence, it can be easily improved and customized.

# Chapter 4: Design of a MAS-based Framework for SCN modeling

## 4.1. INTRODUCTION

The literature review performed in the previous chapter has provided some key features in the design of MAS. This chapter describes the design of a MAS-based framework for SCN modeling, which is based on all the valuable information gathered during the review process. First, the two-layer design of the framework is introduced. After that, a detailed description of each layer is provided.

Real SCNs have multiple layers of abstraction (Lin *et al*., 2002) and they can be studied in different levels of details. Hence, in order to model complex SCNs, the framework must be either able to accurately model the internal processes that take place inside the enterprises as well as modeling large SCNs with many of these enterprises. Thus, a two-layer design has been chosen: an Enterprise Layer containing all enterprises in the SCN, and a Functional Layer, including the main functions/departments of the enterprises. This framework design will allow studying inter-enterprises relationships and intra-enterprises relationships.

In order to simplify the framework and reduce the number of agents, the Enterprise Layer is modeled by one generic and reusable agent (Enterprise Agent), instead of using one different agent to model different enterprises. The behavior of this generic agent is customized according to the role that the enterprise plays in the SCN. Its behavior is modeled by a collection of several functional agents (Functional Layer), which model physical and planning tasks, thus building a nested agent structure (see Figure 4.1). By doing this, every department in the enterprise is encapsulated in one agent, with its characteristics of independency and autonomy, and being able to take its own decisions. In accordance with the bottom-up methodology (a central feature of MAS), the SCN and the Enterprise Agent are not explicitly modeled. Instead, the Enterprise Agent behavior emerges from its components' behaviors (i.e., functional agents), which are easier to understand and model. Similarly, the global SCN behavior emerges from that of its components enterprises.
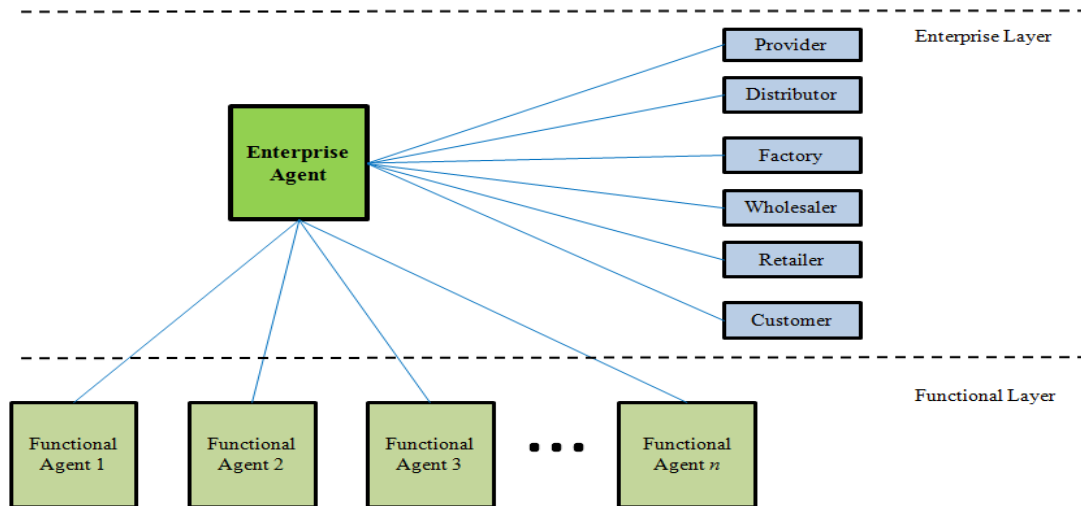
**Figure 4.1.** Two layer MAS framework design.

According to this methodology, a bottom-up description of the framework is provided next, starting with the functional agents and then, describing how they can be combined within the Enterprise Agent to adopt different roles.

## 4.2. FUNCTIONAL AGENTS

A good design of the functional layer is crucial because functional agents must capture the internal dynamic of a real enterprise and should model the key aspects of enterprise management. The initial design of the functional layer is based in the level 1 of the SCOR model (SCC, 2006) and the literature revised. Each one of the physical activities of SCOR (with the exception of Return) is modeled by one independent agent, so there are three physical agents: Source Agent, Make Agent and Deliver Agent. The Return activity is implicitly implemented by allowing the Deliver Agent to return products or receive returned products. According to the Supply Chain Planning Matrix in Stadtler (2005), the Plan activity has been divided into six planning functions, being each of these functions carried out by a different functional agent: Demand Fulfilment Agent, Demand Forecast Agent, Master Planning Agent, Production Planning Agent, MRP (Material Resource Planning) Agent and Scheduling Agent.

The functional layer of an enterprise can be then modeled by a mix of planning agents and physical agents. Planning agents store management policies and take the main decisions. Physical agents control the physical resources of the enterprise and

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share information with planning agents. Table 4.1 summarizes the functional agent framework.

**Table 4.1.** Functional agents framework.

| Category | SCOR model | Planning Matrix (Stadtler, 2005) | Agents | Main Tasks |
|---|---|---|---|---|
| Planning Activities | Plan | Demand Fulfilment & ATP | Demand Fulfilment Agent | Demand management Communication with customers |
| | | Purchasing & Material Requirements Planning | MRP Agent | Purchase management Communication with providers |
| | | Demand Planning | Demand Forecast Agent | Demand forecast |
| | | Master Planning | Master Planning Agent | Aggregate production planning |
| | | Production Planning | Production Planning Agent | Disaggregate production planning |
| | | Scheduling | Scheduling Agent | Jobs sequence |
| Physical Activities | Source | - | Source Agent | Reception and storage of raw materials |
| | Make | - | Make Agent | Manufacturing process (machines) |
| | Deliver | - | Deliver Agent | Storage of finished products and delivery to customers |
| | Return | - | | |

A brief description of the agents is presented below:

- Source Agent. It handles the arrival and storage of raw materials, and its delivery to the manufacturing process when needed.

- Make Agent. It monitors the manufacturing process by controlling machines and the flow of jobs in the shop floor.

- Deliver Agent. It handles the arrival and storage of finished products, and the delivering of orders to customers.

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- Demand Fulfilment Agent. It is in charge of demand management and inventory control. It checks incoming RFQs (Request for Quotations) from customers and quotes the due dates. If the order is accepted, it tries to fulfil them from inventory, if available. If inventory is not enough, it sends a production order (a Job) to the Scheduling Agent if the enterprise is a manufacturer. Otherwise it sends a purchase order to the MRP Agent.

- Demand Forecast Agent. It requests the enterprise demand historical data to the Demand Fulfilment Agent in every forecast period. Then it forecasts the demand for each product in the next periods using a forecasting rule (like Simple Moving Average, Exponential Smoothing, etc.).

- Master Planning Agent. It uses forecast information from the Demand Forecast Agent and generates an aggregate Master Plan for the products concepts defined by the enterprise by solving a linear programming model (that includes capacity and inventory restrictions, as well as production and inventory holding costs), obtaining the production needs per product concept for each period.

- Production Planning Agent. It receives the Master Plan and uses it to generate a detailed Production Plan, obtaining the production needs for the final products to accomplish the Master Plan.

- MRP Agent. It creates a detailed material plan to fulfil the Master Plan. If there is no Master Plan, it takes control of the raw material inventory levels by using some inventory policy. This agent is in charge of the purchases in the enterprise.

- Scheduling Agent. It schedules production orders (Jobs) coming from the Production Planning/Demand Fulfilment Agent by using first some priority rule to create an initial solution, and then a heuristic to improve the initial solution according to certain objective. It also calculates start and end times for each job (so it can help the Demand Fulfilment Agent for due date calculation), generating a detailed schedule. According to this schedule, at the starting time of each job it sends the job information to the Make Agent to start its production.

The overall configuration of a generic enterprise, with all its functional agents is shown in Figure 4.2.
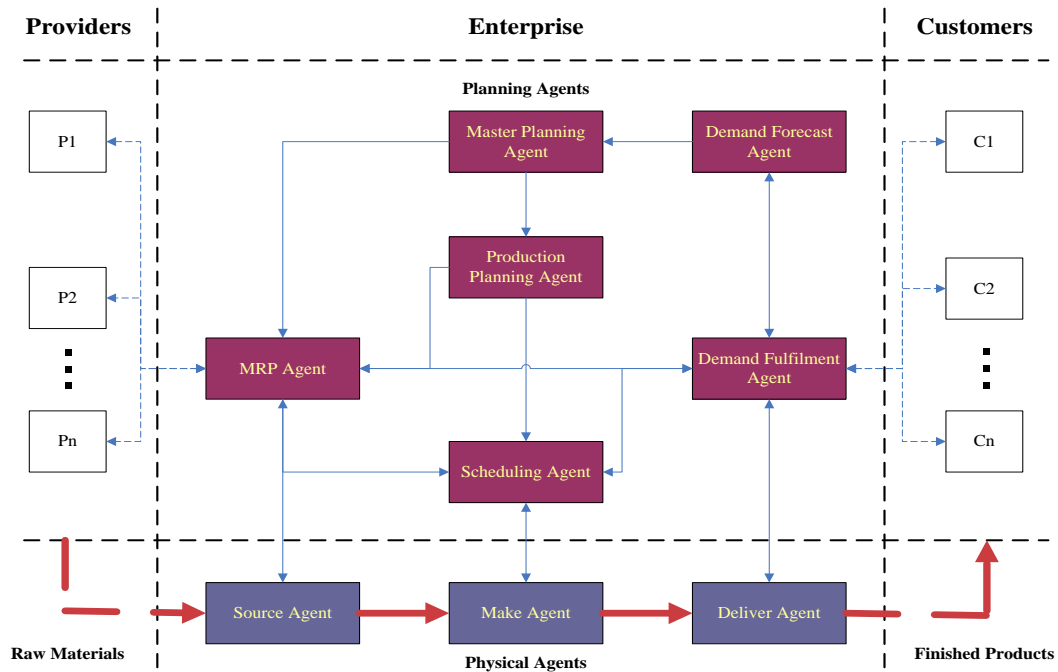


**Figure 4.2.** Multi-Agent Framework: functional layer display of a generic enterprise.

## 4.3. ENTERPRISE AGENT

The Enterprise Agent is able to model any kind of enterprise in the SCN: Suppliers, Manufacturers, Distributors, Retailers, etc. To do so, it can be customized by a combination of different functional agents, which determines the global behavior of the Enterprise Agent and its role in the SCN. Enterprises with similar functions (in terms of functional agents) belong to the same category. The identification of these roles is based on Röder and Tibken (2006): the basic role of an enterprise is determined by its combination of structural agents. These authors identified the following roles:

- The SMD-enterprise type (Source-Make-Deliver) represents an enterprise that contains the whole intra-enterprise process chain including source, make and deliver processes.

- The MD-enterprise (Make-Deliver) is similar to the SMD-enterprise, have no inventory for incoming goods. The material coming from the suppliers is

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delivered directly into the production process by "just-in-time" or "just-in-sequence" strategies.

- The SD-enterprise (Source-Deliver) does not have production processes. This enterprise is represented by sourcing and delivering processes, having an inventory for incoming goods.

According to the above classification, four roles can be adopted by the Enterprise Agent:

- Factory, based on the SMD-enterprise for modeling Manufacturers and Assemblers type enterprises. This role needs the entire physical agents for sourcing raw materials, making new products and delivering them to customers, and three planning agents for managing orders and purchases, as well as scheduling production. Optionally, they can include forecasting and production planning abilities.

- Intermediary, based on the SD-enterprise for modeling Distributors, Wholesalers and Retailers type enterprises. This role needs one physical agent to store and deliver products, and two planning agents for managing orders and purchases. Optionally, they can include forecasting abilities.

- External Provider, which is a simplification of the SD-enterprise for modeling Providers type enterprises that are out of the SCN (Source is not required). This role needs a physical agent to deliver products to members of the SCN and a planning agent to manage the orders received.

- External Customer, which is a simplification of the SD-enterprise for modeling Customers that are out of the SCN (Deliver is not required). This role needs a physical agent to source products from members of the SCN and a planning agent to manage the orders placed to them.

A summary of these roles is provided in Table 4.2.

In order to model a new enterprise with this framework, it is enough to select one of the roles from Table 4.2 for the Enterprise Agent and automatically the required functional agents are assigned to it. The basic agents always belong to the Enterprise Agent for the selected role, while the optional agents are selected depending on the enterprise characteristics. Although the roles included in the framework should be enough to model all kind of enterprises in the SCN, it might be possible to create new

roles in case of necessity by selecting a different combination of functional agents for the Enterprise Agent and/or adding new functions to the functional agents.

**Table 4.2.** Roles of the Enterprise Agent.

| Roles in Framework | Description | Examples types | Enterprise type (Röder and Tibken, 2006) | Basic Agents | Optional Agents |
|---|---|---|---|---|---|
| Factory | The enterprise is in the SCN and has manufacturing or assembly capacity | Manufacturer, Assembler | SMD-type | Demand Fulfilment, MRP, Scheduling, Source, Make, Deliver | Demand Forecast, Master Planning, Production Planning |
| Intermediary | The enterprise is in the SCN and has not manufacturing or assembly capacity | Distributor, Wholesaler, Retailer | SD-type | Demand Fulfilment, MRP, Deliver | Demand Forecast |
| External Provider | Any enterprise who provide something to the SCN, but it's out of the SCN | Provider | - | Demand Fulfilment, Deliver | No |
| External Customer | Any enterprise who demand something to the SCN, but it's out of the SCN | Customer | - | MRP, Source | No |

## 4.4. SUMMARY AND CONCLUSIONS

This chapter describes the design of a MAS-based framework for SCN modeling, which takes use of the knowledge obtained from the literature review on MAS applications to SCN modeling described in the previous chapter. Summarizing, the designed framework presents the following highlights:

- ✓ It presents a simple agent structure, with one generic agent modeling all type of enterprises in the SCN and a collection of functional agents to carry on the main functions of the enterprise. These functions include the three main physical functions (source, make and deliver) and a planning function, according to SCOR (SCC, 2006), and the planning function has been divided into six sub-functions according to the Supply Chain Planning Matrix from Stadtler (2005).

- ✓ It is intuitive, since each functionality or department is encapsulated in one different agent. Furthermore, this modular design allows to easily improving and

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customizing each functional agent independently, focusing on the particular function of interest.

- ✓ The two-layer design allows analyzing inter-enterprise as well as intra-enterprise processes.

- ✓ The reusability and customizability of the Enterprise Agents allows quickly creating a high number of enterprises with different roles, connecting them and obtaining large SCNs, making possible the analysis of complex SCN structures.

# Chapter 5: Framework implementation. A SCN simulation tool: SCOPE

## 5.1. INTRODUCTION

In the previous chapter, a MAS-based framework for SCN modeling has been developed. It uses many concepts of previous works found in literature and discussed in Chapter 3 to ensure an accurate modeling of the SCN processes as well as flexibility and modularity. In order to be able to use it to provide results, the framework has to be implemented in a MAS simulation package. Furthermore, it has to be tested and compared with other models to ensure that the results offered by SCOPE are accurate. In this chapter, a description of the simulation package used and the implementation of the framework are provided, as well as a validation test with several models found in literature.

## 5.2. MAS SIMULATION TOOLS

There are many options in choosing a MAS software platform. Most of the commonly used MAS platforms follow the "framework and library" paradigm, providing a framework (a set of standard concepts for designing and describing MASs) along with a library of software implementing the framework and providing simulation tools (Railsback *et al*., 2006). Some of the most commonly used MAS platforms are summarized next:

▪ Swarm (Minar *et al*., 1996). The initial version of the library of Swarm was written in Objective-C. Later, a Java version of Swarm was developed, in which a set of simple Java classes allowed use of the Swarm's Objective-C library from Java. It was designed as a general language and toolbox for MAS, intended for widespread use across scientific domains. A key concept of Swarm is the *swarms*, which help in organizing models at different levels of detail.

▪ Repast. Its initial design started as a Java implementation of Swarm, but it diverged significantly. Repast did not adopt all of Swarm's design philosophy and does not implement swarms. It was also clearly intended to support one

domain (social science in particular). Furthermore, the schedule executes top-level actions in randomized order (which is not desirable), while Swarm allows a precise control of the sequence of actions.

- MASON (Multi-Agent Simulator of Networks) (Luke *et al.*, 2005). It was designed as a smaller and faster alternative to Repast, with a clear focus on computationally demanding models with many agents executed over many iterations. However, MASON is the least mature of these platforms, with only a few basic capabilities and a complex programming language.

- Netlogo. Its primary design objective is clearly ease of use. With a programming language that includes many high-level structures and primitives, it greatly reduces programming effort. However, the language contains many but not all the control and structuring capabilities of a standard programming language. Further, NetLogo was clearly designed with a specific type of model in mind: mobile agents acting concurrently on a grid space with behavior dominated by local interactions over short times, and that are not extremely complex.

There are many other tools for MAS design, like JADE, Zeus, JACK, ADE, Anylogic, etc.

SCOPE has been implemented in Swarm (Swarm Development Group Wiki, 2003) Java version, using NetBeans IDE 6.7 as implementation framework. Swarm has been chosen due to its high maturity, its model organization (nested *swarms*), which helps in modeling SCNs, its generic and low-level programming language (Java), and its suitability for modeling CAS (Minar *et al.*, 1996) and SCNs (Lin *et al.*, 1998). It provides object oriented libraries of reusable components for building models and analyzing, displaying, and controlling experiments on those models. A comparison of similarities between SCN's features and Swarm can be seen in Table 5.1.

For solving the planning models included in the Master Planning and Production Planning agents (see Chapter 4), SCOPE can be connected with Gurobi solver through a special library for Java. Gurobi is a commercial software package for solving large-scale mixed-integer linear optimization problems.

In the next section, a description of the Swarm modeling paradigm is provided.

**Table 5.1.** A comparison between SCNs and Swarm (adapted from Lin *et al.*, 2002).

| SCNs | Swarm |
|---|---|
| Composition of autonomous and semi-autonomous business entities | A swarm of agents with individual based modeling |
| Business entities act different organizationally | Agents are constructed with internal state variables and action functions |
| Multiple layer abstraction | Nested inherent hierarchy |
| Information flows between business entities | Message passes between agents |
| Material flow during procurement, manufacturing, and distribution activities | Discrete event simulation and time-stepped scheduling to trigger agent actions |
| Global performance contributed by the processes of individual entities | Collective behaviour contributed by the combination of individual behaviours |
| Visibility determined by the information boundary | Visibility determined but the boundaries of message passing |

## 5.3. SWARM MODELING TOOL

The modeling formalism that Swarm adopts is a collection of independent agents interacting via discrete events triggered by schedules. Within that framework, Swarm makes no assumptions about the particular sort of model being implemented. The basic unit of a Swarm simulation is the agent: any actor in the system, any entity that can generate events that affect itself and other agents. A schedule is a data structure that combines actions in the specific order in which they should execute. The passage of time is modeled by the execution of the events in some sequence. Simulations consist of groups of many interacting agents.

The fundamental component that organizes the agents of a Swarm model is a "*swarm*", a collection of agents executing a schedule of actions. Swarm supports hierarchical modeling approaches whereby agents can be composed of *swarms* of other agents in nested structures. The ability to build models at various levels of detail can be very powerful. In addition to being containers for agents, *swarms* can themselves be agents. In this case, the agent's behavior is defined by the emergent phenomena of the agents inside its *swarm*. The *swarm* represents an entire model: it contains the agents as well as the representation of time (schedules). Measurement happens by the actions of observer agents, special objects whose purpose it is to observe other objects. The observer agents themselves are a *swarm*, a group of agents and a schedule of activity.

By combining this *swarm* with a model *swarm* running as a sub-*swarm* of the observer, a full experimental apparatus is created. The hierarchical modeling has been exploited in the development of SCOPE in order to implement the two-layer design explained in Chapter 4.

Swarm libraries are written in Java, an object oriented language. An object is a combination of instance variables for the object's state and methods that implement the object's behavior. In Swarm, an agent is modeled directly as an object. Types of agents are classes, and specific agents are objects, instances the class. Each object carries with it its own state variables, but the generic definition of its behavior is provided by the class, in the form of methods. These methods are triggered by the schedules in a predetermined order, determining the sequence of actions.

A summary of the main packages included in Swarm is provided next:

- *swarmobject*: it contains classes for modeling agents and *swarms*.

- *activity*: it contains the heart of the simulation mechanism, the scheduling data structures and execution support.

- *simtools*: it contains classes to control the execution of the entire simulation apparatus.

- *collections*: it implements the container classes used to track objects in a system: maps, lists, sets, etc.

- *random*: it contains a suite of random number generators

- *defobj*: it defines the infrastructure for the Swarm object model

All the above packages along with the classes included in Swarm is summarized in a documentation file provided with the simulation software. Further information about Swarm can be found in the website: http://www.swarm.org.

## 5.4. FRAMEWORK IMPLEMENTATION BY SWARM

This section describes the implementation of the framework developed in Chapter 4 using Swarm. The obtained implementation results in a set of four different objects, nine agents, three swarms, and a collection of configuration files. All these components are briefly described below. After that, an overall description of the final configuration

of SCOPE, the code generated and a summary of its main modeling characteristics are provided.

### 5.4.1 Components

#### 5.4.1.1. Objects

The objects are special artifacts created to help in the simulation. They are information containers created by the agents, who use them and send them to other agents. These objects are the following ones:

- RFQ: agents use this object to store information about orders, like the type of product desired, quantity, requester ID, etc.

- Job: agents use this object to store information about production orders within his enterprise, containing information about the type of product, quantity, processing times, material needs, etc. The Jobs are then scheduled (by the Schedule Agent) and at the starting time are sent to the Make Agent.

- Product: these objects represent the physical products and raw materials.

- Machine: these objects are created by the Make Agent at the beginning of the simulation. They model the different machines in the shop floor, and contain information about the status (busy or free), the jobs in queue, the job being processed, etc.

A typical object in SCOPE is represented by a generic class, where all the variables and methods are defined. The methods available in the objects classes are there only for checking and changing the values of their own internal variables.

#### 5.4.1.2. Agents

Agents are the basic elements in the simulation model. They represent the main functions in the enterprise (functional agents in the framework). Their behavior is modeled by writing methods. Information is passed by arguments, which makes easy to add new capabilities to the agents by simply adding new methods, or by overwriting existing ones. A typical agent is represented by a java class that extends the Agent class in Swarm. A pseudo code example is shown below:

```
Public class DemandFulfilment extends SwarmObjectImpl {
//Internal Variables
Private String enterpriseID;
Private String materials [][];
Private boolean batch;
Private int [] rs;
Private int [] QS;
...
//Constructor
Public DemandFulfilment (String enterpriseID, boolean batch, int [] rs, int []
QS,...) {
this.enterpriseID = enterpriseID;
this.batch = batch;
this.rs = rs;
this.QS = QS;
...
}
/*Methods: define behaviours and abilities of the agent*/
Public void checkRFQlist (ArrayList<RFQ> RFQlist, Deliver deliver, ...) {...}
Public void deliverInvManagement (Deliver deliver, MRP mrp, ...) {...}
...}
```

### 5.4.1.3. Swarms

Since the framework was constructed using a two-layer design (see Chapter 4), there is a *swarm* containing all the functional agents, which constitutes an enterprise (Enterprise *swarm*), and another *swarm* containing all the enterprises in the SCN, which constitutes the SCN or the model (Model *swarm*). A third *swarm* helps in the simulation (Observer *swarm*). The three *swarms* are summarized next:

▪ Enterprise *swarm*: this is the main *swarm*, and it serves to model an entire enterprise. It is formed by a combination of the nine types of agents described before and contains the schedules for all these agents, controlling their actions. The behavior of the enterprise *swarm* is defined by the emergent phenomena of the agents inside themselves.

▪ Model *swarm*: it models the SCN environment, containing all the enterprises and schedules to control the communication between enterprises. Thus, the behavior of the SCN, instead of being predetermined, emerges by the interaction of the enterprises.

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- Observer *swarm*: it contains the model *swarm* and special methods to gather and present all relevant information from the agents in the model swarm, for a post-simulation analysis.

### 5.4.1.4. Configuration files

The last components of the implementation are the configuration files. These are text files in which user introduces all relevant data of the target SCN and thus, customizing the generic structures of the agents. The available configuration files are summarized next:

- *SC_generalData*: describes the general behavior of the enterprises. Ordering policies, inventory policies, initial inventory levels, forecasting rules, etc. are defined here.

- *SC_structureData*: describes the structure of the SCN. The customers and providers of each member of the SCN are defined here.

- *SC_productData*: describes the manufacturing characteristics of the different products in the SCN. The requirements of materials for each product (Bill of Materials), the route through the different machines in the shop floor, as well as the processing times in each machine are defined here.

- *SC_planningData*: describes the information needed for the master planning and the production planning models.

- *SC_uncertaintyData*: describes the different uncertainties of the SCN, such as lead times, demand variability or machine process times.

- *SC_analysisData*: the user defines the information to be collected after the simulation in order to be analyzed.

### 5.4.2. Overall

In order to facilitate the comprehension of the model and, in particular, the relation between the framework and the Swarm implementation, an example is provided below.
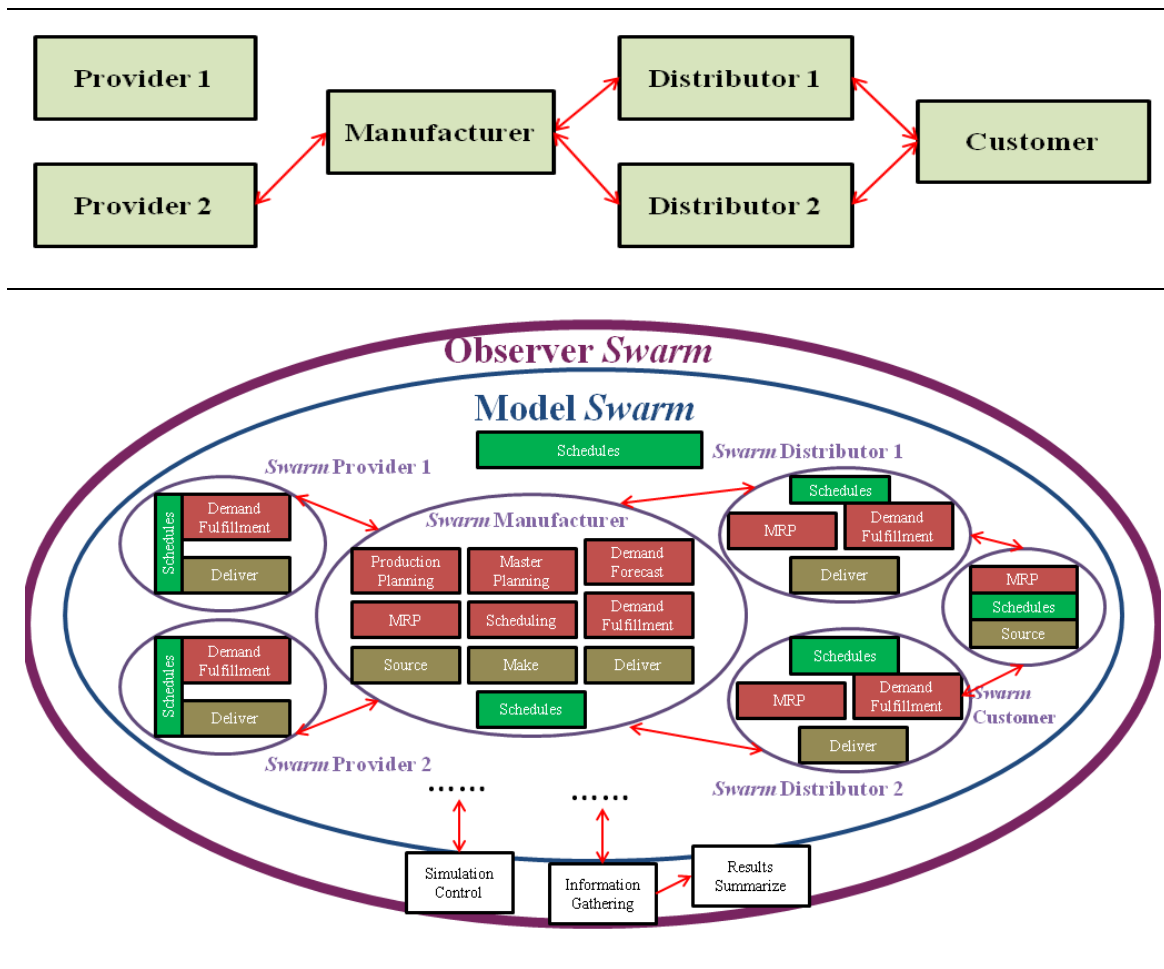
**Figure 5.1.** Modeling a simple SCN with SCOPE using the Swarm modeling paradigm.

In this example, a simple SCN with two providers, one manufacturer, two distributors and one customer is graphically modeled (Figure 5.1).

Figure 5.2 shows a screenshot of the NetBeans IDE with the SCOPE project opened and running an experiment. The window is divided in four sub-windows and two menus, which are briefly explained below:

- Top-left sub-window: a navigator showing all the classes and configuration files included in the SCOPE folder.

- Top-right sub-window: it shows the contents of the selected file. Here is where the user can edit all the classes and configuration files.

- Bottom-left sub-window: it summarizes all the variables and methods of the class selected.

- Bottom-right sub-window: agents report their actions during the simulation in this sub-window. Each message starts with the current simulation step, followed by the name of the company and a coded name for the agent performing the action.

- Process Control menu: it controls the simulation process.

- Observer Swarm menu: user can modify in this menu some simulation parameters before the simulation starts.
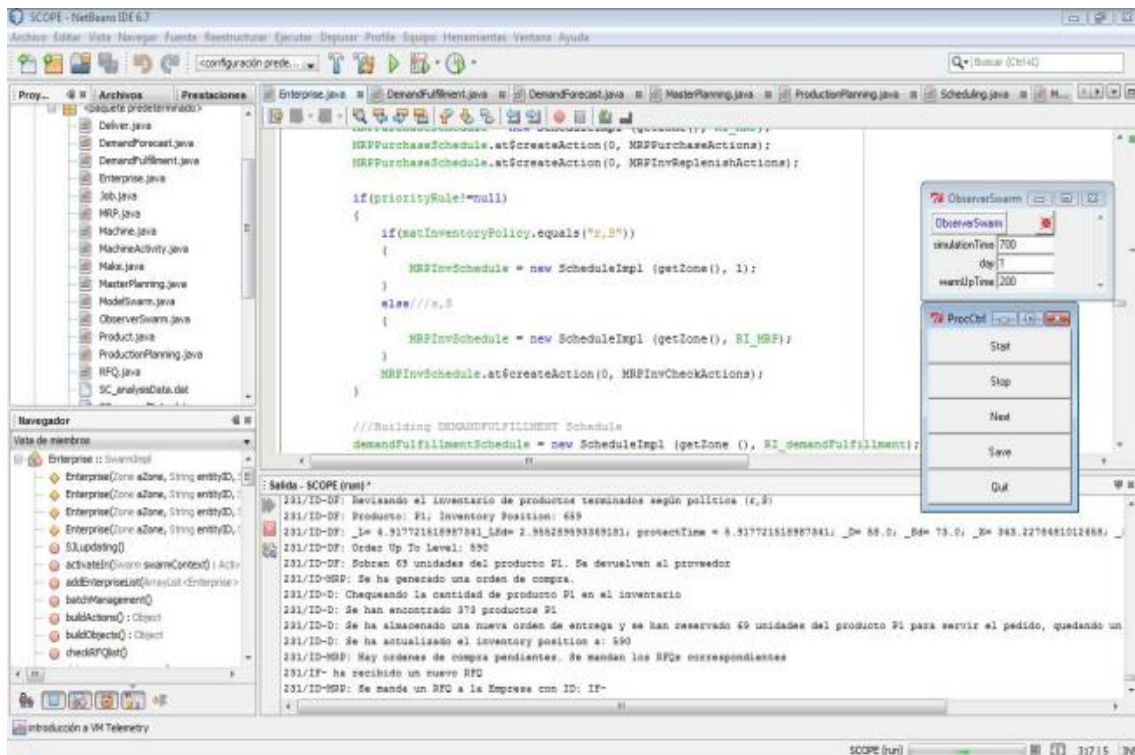


**Figure 5.2.** A snapshot of the SCOPE project.

The source code of SCOPE has been analyzed by Code Analyzer 0.7.0, which is a software source file metrics application. The implementation of SCOPE has resulted in a total of 20 classes and 6,785 code lines (see Figure 5.3 left). Furthermore, 1,518 comments lines have been added in order to facilitate the understanding of SCOPE to new users and make it easier to be improved. In addition, 12 new classes and 3,879 code lines have been added during the development of this Thesis (see Figure 5.3 right), in order to help with collecting data and obtaining different metrics for the BWE, organizing output data for statistical analysis (ANOVA), running multiple experiments automatically, randomly generating different SCNs structures, etc.

Since the resultant simulation software has been built-up from its initial design phase around a generic SCN modeling tool concept, it can be used to research on a wide variety of topics within the SCM, as it can be seen from Table 5.2 where the main modeling characteristics of the current version of SCOPE are summarized.

**Table 5.2.** Modeling characteristics of SCOPE.

| | |
|---|---|
| **Enterprises** | • Unlimited number of fully customizable enterprises<br>• Four roles: Manufacturer, Intermediary, External Provider, External Customer |
| **Products** | • Unlimited number of different products<br>• Individual manufacturing characteristics (processing times, raw material requirements, shop floor machine routes)<br>• Individual inventory control policies |
| **SCN structure** | • Total flexibility in modeling different SCN structures (serial, convergent, divergent, conjoined, etc.) |
| **Demand control policies** | • *Make-to-Order* (MTO): Online orders and batching<br>• *Make-to-Stock* (MTS): $(r,S)$, $(s,S)$ and $(r,Q)$ policies<br>• *Assemble-to-Order* (ATO) |
| **BWE avoidance** | • Information sharing, smoothing OUT |
| **Shop floor** | • Individual shop floor configuration for each manufacturer (*Job-shop & Flow-shop* configurations)<br>• Unlimited number of different processing machines |
| **Production scheduling** | • Scheduling priority rules (FCFS, SPT, LPT)<br>• Optimizing *makespan* and *flowtime* by heuristics (Greedy) |
| **Production planning** | • Aggregate master planning and detailed production planning<br>• Solving planning models by an external connection with Gurobi solver |
| **Uncertainties** | • Machine processing time, Lead time, External demand, External supply |
| **Demand forecast** | • Simple Moving Averages (SMA), N-Periods Moving Averages (NPMA), Weighted Moving Averages (WMA), Simple exponential smoothing (SES) |
| **Random distributions** | • Uniform, Normal, Poisson, Exponential, Gamma |
| **Other** | • Random external demand according to distribution<br>• Step demand (step in demand mean)<br>• Reverse Logistics (allowing to return products)<br>• Inventory record data errors<br>• Due dates |

**Results for src**

| | | | |
|---|---|---|---|
| 100% | 80% | 18% | 8% |
| 8519 | 6785 | 1518 | 672 |
| Total | Code | Comment | Whitespace |

**Results for test**

| | | | |
|---|---|---|---|
| 100% | 91% | 4% | 6% |
| 4282 | 3879 | 161 | 273 |
| Total | Code | Comment | Whitespace |

| Metric | Value |
|---|---|
| Total Files | 20 |
| Total Lines | 8519 |
| Avg Line Length | 40 |
| Code Lines | 6785 |
| Comment Lines | 1518 |
| Whitespace Lines | 672 |
| Code/(Comment+Whitespace) Ratio | 3,10 |
| Code/Comment Ratio | 4,47 |
| Code/Whitespace Ratio | 10,10 |
| Code/Total Lines Ratio | 0,80 |
| Code Lines Per File | 339 |
| Comment Lines Per File | 75 |
| Whitespace Lines Per File | 33 |

| Metric | Value |
|---|---|
| Total Files | 12 |
| Total Lines | 4282 |
| Avg Line Length | 32 |
| Code Lines | 3879 |
| Comment Lines | 161 |
| Whitespace Lines | 273 |
| Code/(Comment+Whitespace) Ratio | 8,94 |
| Code/Comment Ratio | 24,09 |
| Code/Whitespace Ratio | 14,21 |
| Code/Total Lines Ratio | 0,91 |
| Code Lines Per File | 323 |
| Comment Lines Per File | 13 |
| Whitespace Lines Per File | 22 |

**Figure 5.3.** Source code analysis.

## 5.5. VALIDATION OF SCOPE

In order to validate SCOPE a literature review has been done, looking for SCNs that have been already modeled and simulated by other authors and comparing their results with those provided by SCOPE. The selected work must be published in an important journal and it must provide enough information to reproduce the experiments. Chatfield *et al*. (2004) validated their software SISCO by comparing their results with those by Chen *et al*. (2000) and Dejonckheere *et al*. (2003a). Since they provide enough information to reproduce the validation experiments and use a double comparison with two well-recognized works, SCOPE has been validated using the same procedure described in Chatfield *et al*. (2004). Furthermore, a third validation scenario has been performed, reproducing some of the experiments conducted in Chatfield *et al*. (2004) after the validation of SISCO.

The SCN's structure is the same for the first two scenarios (Figure 5.4). There is only one product in the SCN, and it is structured by a serial formation of customer, retailer, wholesaler, distributor, and factory levels. The lower node places orders with the next upper node and this node fills these orders. The customer does not fill orders and the factory places orders with an outside supplier.
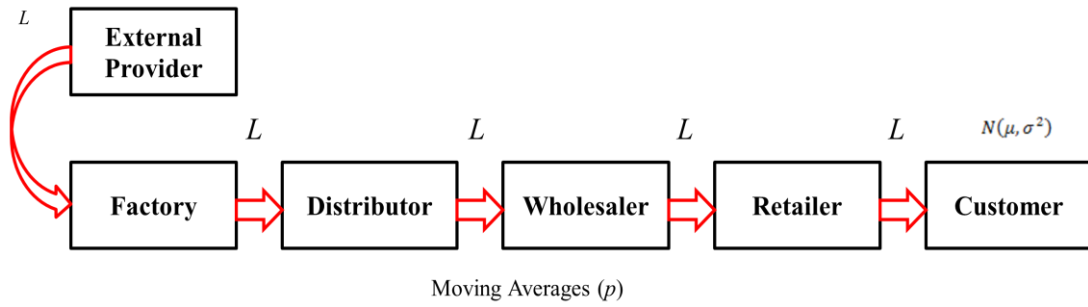
Figure 5.4. Serial SCN modeled by Chen *et al.* (2000) and Dejonckheere *et al.* (2003a).

There are other characteristics that remain identical for both scenarios:

- Lead Time: there is a fixed lead time between the time an order is placed at a stage *i* and when it is received at that stage, such that an order placed at the end of period *t* is received at the start of period *t+L*.

- Customer Demand: these are normally distributed. Negative demands are allowed.

- Demand Forecast: enterprises use *p*-periods moving average (all enterprises use the same "*p*" parameter).

- Inventory Policy: Enterprises use a (*r,S*) policy with a review period $r = 1$ and a dynamic OUT level:

$$S = \bar{X} + zs_x \tag{5.1}$$

Where $\bar{X}$ is the estimated demand over the protection time $L + r$. For simplicity $z = 0$, so if $\bar{D}$ is the demand estimation, the OUT level is given by the following equation:

$$S = \bar{X} = (L + r)\bar{D} \tag{5.2}$$

If the inventory level is lower than the $S$ level, enterprises are allowed to return goods.

### 5.5.1. Scenario 1: Chen *et al.* (2000)

Chen *et al.*'s (2000) coining of the Order Rate Variance Ratio (ORVR) as the quantification metric for demand amplification along a SCN could reasonably be considered the starting point of the current research period in this domain (Cannella and Ciancimino, 2010). They calculated a statistical lower bound for the order variance amplification. For the SCN described above, the proposed lower bound is given by equation (5.3).

$$\frac{Var(q^k)}{Var(D)} \geq \prod_{i=1}^{k}\left(1 + \frac{2L_i}{p} + \frac{2L_i^2}{p^2}\right), \forall k \qquad (5.3)$$

Results obtained are very close to those offered by SISCO, although greater amplifications than Chen *et al.* (2000) results have been found at upper SCN stages. Chatfield *et al.* justify these results arguing that the bounds provided by Chen *et al.* do not account for interactions and interdependencies present in a multi-stage system. To test this, they perform a "sequential pairs execution" simulation, in which they broke the SCN into four two-node sub-chains (customer-retailer, retailer-wholesaler, wholesaler - distributor, distributor - factory). Then, they simulate each sub-chain using the ordering mean and standard deviation obtained from the simulation of the previous sub-chain. This new scenario has been simulated by SCOPE, obtaining the results in Table 5.3, which are extremely close to those predicted by Chen *et al.*, and SISCO.

**Table 5.3.** Amplification Ratio for Chen *et al.* (2000). Parameters: demand rate = $N(50, 20^2)$; protection time = $L+R$ = 4+1 = 5; *NPMA*(15) forecasting; simulation time = 5200 time periods (200 for warm-up).

| Enterprise | Chen *et al.* | SISCO | SCOPE |
|:---:|:---:|:---:|:---:|
| Retailer | 1.89 | 1.90 | *1.90* |
| Wholesaler | 3.57 | 3.59 | *3.53* |
| Distributor | 6.74 | 6.70 | *6.66* |
| Factory | 12.73 | 12.84 | *12.58* |

### 5.5.2. Scenario 2: Dejonckheere *et al*. (2003a)

In Dejonckheere *et al*. (2003a), authors proposed another measure for the order variance amplification using a Control Engineering methodology. Considering a SCN with the same characteristics that the one described before, they obtained the result shown in equation (5.4).

The results obtained for this scenario are summarized in Table 5.4, where it can be noted that SCOPE performs very similar to SISCO and to Dejonckheere *et al*. (2003a).

$$TF_n = \left[\frac{-2 - Tp + 2z^{Tm} + Tmz^{Tm} + Tpz^{Tm}}{Tmz^{Tm}}\right]^n \qquad (5.4)$$

**Table 5.4.** Amplification Ratio for Dejonckheere *et al*. (2003a). Parameters: demand rate = $N(100, 10^2)$; protection time = $L+R$ = 3+2 = 5; *NPMA*(19) forecasting; simulation time = 5200 time periods (200 for warm-up).

| Enterprise | Dejonckheere *et al.* | SISCO | SCOPE |
|:---:|:---:|:---:|:---:|
| Retailer | 1.67 | 1.67 | *1.71* |
| Wholesaler | 2.99 | 2.99 | *3.10* |
| Distributor | 5.72 | 5.72 | *5.96* |
| Factory | 11.43 | 11.43 | *11.93* |

### 5.5.3. Scenario 3: Chatfield *et al*. (2004)

After the validation of SISCO, in Chatfield *et al*. (2004) authors analyzed the impact of information sharing and different degrees of information quality on the BWE when the lead time between enterprises is stochastic. The SCN used is similar to the one used in the previous scenarios, with only some differences:

- Lead Time: is stochastic and gamma distributed, and the mean lead times at the customer, retailer, wholesaler, distributor, and factory are 0, 4, 4, 4, and 4 time units, respectively.
- Customer Demand: negative demand is not allowed.

- Inventory Policy: the equation (5.1) is now used with a safety factor of $z = 2.0$ and the experiments are reproduced for three degrees of information quality, named IQL0, IQL1 and IQL2 (IQL stands for Information Quality Level). IQL0 means that enterprises don't update the $S$ level. For IQL1 and IQL2 enterprises use demand rate ($D$) and lead time ($L$) data available to generate forecasts of lead time demand ($\bar{X}$) and variance ($s_x^2$). In the case of IQL1:

$$\bar{X} = (\bar{L} + r)\bar{D} \qquad (5.5)$$

$$s_x^2 = (\bar{L} + r)s_D^2 \qquad (5.6)$$

IQL2 uses lead time variation in the calculation of $s_x^2$, as it appears in equation (5.7):

$$s_x^2 = (\bar{L} + r)s_D^2 + \bar{D}^2 \cdot s_L^2 \qquad (5.7)$$

- Forecast: demand estimation ($\bar{D}, s_D^2$) is doing at each node using a $p$-period moving averages, *NPMA*($p$), and "moving variances," *NPMV*($p$), with $p = 15$. Lead time estimation ($\bar{L}, s_L^2$) is doing at each node using running averages and variances ("all data" approach).

SCOPE is used to reproduce two of the experiments carried out by Chatfield *et al.* for this SCN. The first experiment analyzes the influence of the different information quality levels on the BWE for a lead time *c.v.* = 0.50. The results obtained by SCOPE (see Figure 5.5, above) are very close to those obtained by SISCO in Chatfield *et al.* (2004). The second experiment analyzes the impact of the variance of the lead time on the standard deviation of orders for a given information quality level (IQL2). Again, the results obtained by SCOPE (see Figure 5.5, below) are very close to those obtained by SISCO in Chatfield *et al.* (2004).
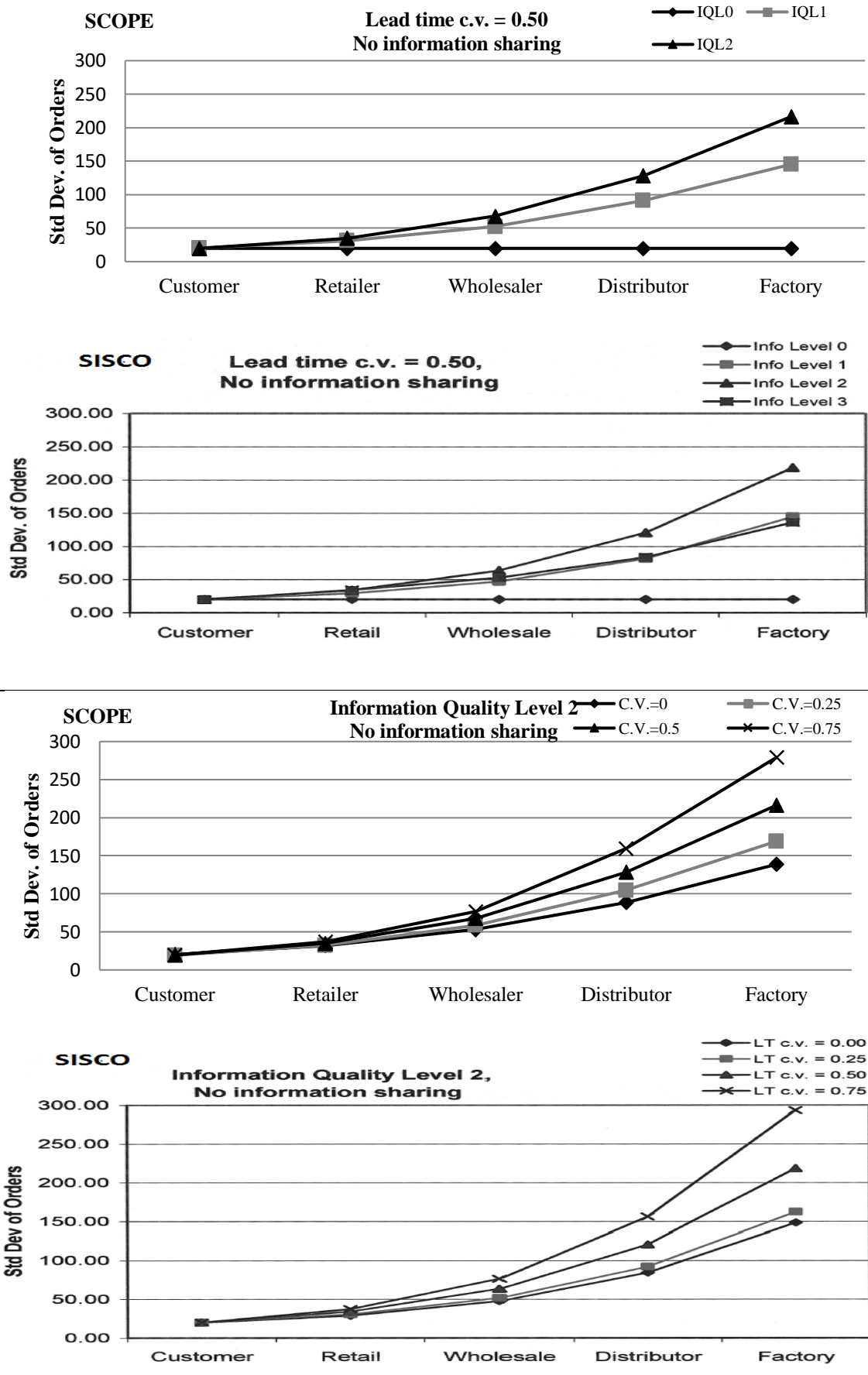
**Figure 5.5.** A comparison between SCOPE and SISCO.

## 5.6. SUMMARY AND CONCLUSIONS

A well-structured framework with a modular design has been developed and implemented in a MAS platform, obtaining a software for SCN simulation that allows modeling a great variety of problems in real-scale SCNs. It is built around the frameworks previously developed by other authors. This tool is useful either for SCN managers or researchers.

Managers often have to take local decisions without knowing in advance the consequences of these decisions on the global SCN, mainly due to the complexity of real SCNs and the many interactions existing between the member enterprises. SCOPE is a powerful tool that allows constructing the global system easily, defining the individual enterprises and their interactions. It might be useful for managers in several ways:

- Improving the understanding of the current SCN configuration, allowing to calculate the global performance of the system, as well as individual performances of target enterprises, considering real disturbances, like stochastic demand, lead times, and more.

- Managers interested in re-engineering the present SCN configuration, implying either structural or operative changes, are able to test several "what-if" scenarios on the SCN model and after the simulations decide which changes are more beneficial for the SCN. If the results obtained do not fulfil the expectations, managers can fine-tune their initial design and improve it by doing several iterations.

- Analysis of the performance in a wide variety of topics within the OFP, like the inventory systems, the planning models, the scheduling rules, the configuration of shop-floors, capacity needs, etc.

- The benefits of collaboration techniques have been proved by several authors (see e.g. Cannella and Ciancimino, 2010; Cannella *et al*., 2011; Ciancimino *et al*., 2012). The distributed nature of autonomous MAS and the structure of SCOPE in two layers (enterprise and functional) allow to implement and test these collaboration techniques on several SCN structure with different levels of details (Domínguez *et al*., 2013), helping managers to decide if its implementation is beneficial or not for the SCN.

Researches can benefit from the open-source code of SCOPE (in Java) and its modular design with the main functions of the enterprises encapsulated in different functional agents to make easier the process of adding new functions, allowing to improve and customize the platform in the desired way.

# PART III

Supply chain' structure
and bullwhip effect

# Chapter 6: Exploring the Bullwhip Effect in divergent SCNs

## 6.1. INTRODUCTION

Part I has fulfilled the first objective of this Thesis: the design and development of a MAS-based SCN modeling tool (SCOPE). In Part II, SCOPE is used to fulfill the second objective of the Thesis: addressing the impact of the structure of SCNs on the BWE. In order to fulfill this objective, one of the most common adopted SCN configuration in the real world is analyzed, i.e. the divergent or arborescent SCN (Beamon and Chen, 2001). Mineral industries and in general consumer-oriented industries, such as cell phone manufacturers, often adopt this typology of SCN (Hung, 2011). This configuration is characterized by a tree-like structure, where every stock point in the system receives supply from exactly one higher echelon stock point, but can supply to one or more lower echelon stock points (Ganeshan, 1999; Hwarng *et al.*, 2005).

More specifically, in this chapter, a comparative analysis between a classical serial SCN with a more complex divergent SCN is performed. To do so, at first, the four-echelon serial SCN structure (i.e. 1 Retailer, 1 Wholesaler, 1 Distributor and 1 Manufacturer) adopted by Chatfield *et al.* (2004) under identical boundary conditions is reproduced. Secondly, a new divergent multi-echelon SCN model (i.e. 8 Retailer, 4 Wholesaler, 2 Distributor and 1 Manufacturer) in which each member is furnished by two downstream members is generated. To perform the analysis, the framework proposed by Towill *et al.* (2007) for studying the BWE is adopted (see Chapter 2). A set of experiments is performed in order to analyze the stationary and the dynamic behavior of both SCNs and results are compared. Finally, results are discussed and some managerial implications are obtained.

## 6.2. SUPPLY CHAIN NETWORK EMPLOYED AS TESTBED

The serial SCN modeled is that of Chatfield *et al.* (2004), described in Chapter 5 for the validation of SCOPE. It consists of four echelons: one factory, one distributor, one

wholesaler, and one retailer (see Figure 6.1). A divergent SCN is characterized by a tree-like structure, where every stock point in the system receives supply from exactly one higher echelon stock point, but can supply to one or more lower echelon stock points (Hwarng *et al*., 2005). The divergent SCN is modeled following the next two guidelines:

1. In order to benchmark both SCNs and to isolate the main effects, the divergent SCN has to be analogous to the serial SCN of Chatfield *et al*. (2004). Hence, the resultant SCN should have identical values of parameters, number of stages (horizontal complexity) and, due to the divergent topology, an increasing number of nodes per stage (vertical complexity), maintaining the symmetry of the SCN.

2. Due to the prospective nature of this work, the resultant divergent SCN must have the minimum complexity. To fulfill with all requirements, each node in the SCN supplies just two nodes downstream.

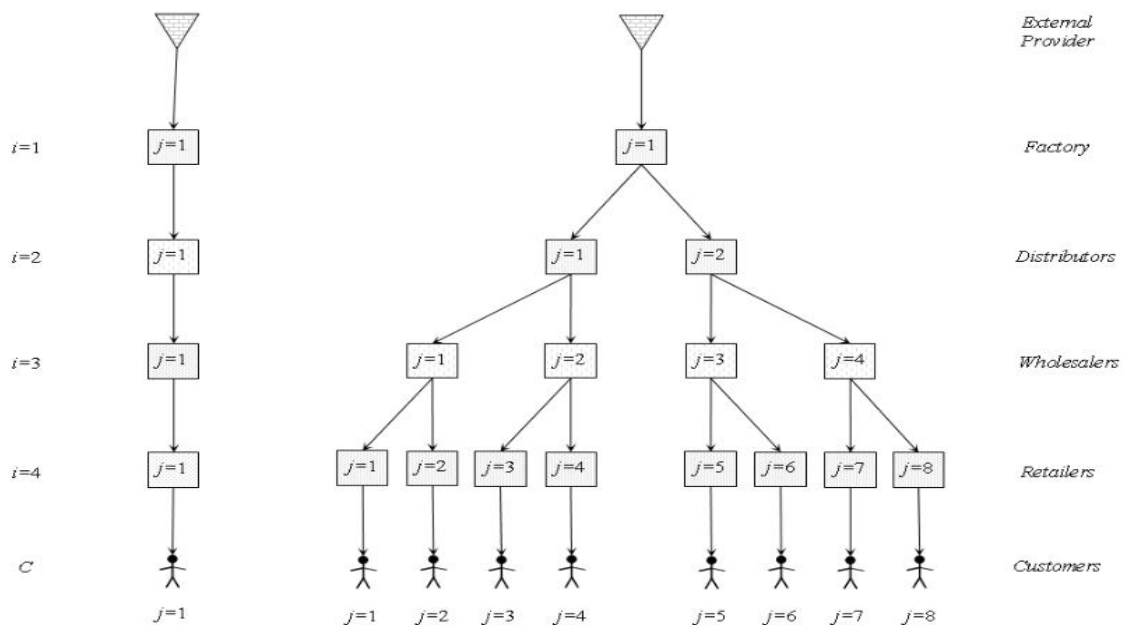The divergent SCN obtained is shown in conjunction with the serial SCN in Figure 6.1.



**Figure 6.1.** Serial vs Divergent SCNs.

The characteristics described in Chatfield *et al*. (2004) for the serial SCN are adapted to the divergent SCN as follows:

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- **Customers Demand**. Each customer demand $(C,j)$ follows the same normal distribution with mean mean $\mu_{C,j}$, estimated by $\overline{D}_{C,j}$, and variance $\sigma_{C,j}^2$, estimated by $s_{C,j}^2$.

- **Lead Time**. The lead time of a node $(i,j)$ $L_{ij}$ is stationary, independent and identically distributed with mean $\mu_{L_{ij}}$ estimated by $\overline{L}_{ij}$, and variance $\sigma_{L_{ij}}^2$ estimated by $s_{L_{ij}}^2$. The lead time of interest or "protection period" in periodic OUT systems, may also include safety lead time or other constant additions to the physical lead time, depending on the inventory policy or other situational characteristics. According to Chatfield *et al.* (2004), all nodes in the SCN use the $(R, S)$ policy (where $R$ is the review period and $S$ is the OUT level) with $R=1$, and the time period of protection is $L_{ij}+R$. The mean lead time is 4 time units for all nodes in the SCN (not including the review period, $R=1$), and 0 for customers. These delays are gamma-distributed, with a coefficient of variation $c.v. = 0.50$.

- **Lead-Time Demand**. Let $X_{ij}^t$ be the demand received by node $j$ in stage $i$ during the protection period $L_{ij}+R$. Then $X_{ij}^t$ has mean $\mu_X$ estimated by $\overline{X}_{ij}^t$, and variance $\sigma_X^2$ estimated by $s_{X_{ij}^t}^2$. Denoting by $D_{ij}^{t+k}$ the demand received by node $j$ in stage $i$ at time $t + k$, $X_{ij}^t$ is obtained for an order placed at time $t$ by the convolution:

$$X_{ij}^t = \sum_{k=0}^{L_{ij}+R} D_{ij}^{t+k} \tag{6.1}$$

- **Inventory Policy and Forecasting**. The OUT level, $S_{ij}^t$, is the base stock that allows the system to meet the demand during the time period $L_{ij}+R$:

$$S_{ij}^t = \overline{X}_{ij}^t + z s_{X_{ij}^t} \tag{6.2}$$

Thus, at the beginning of every period $t$, each node $j$ in stage $i$ will place an order to raise or lower the inventory position to $S_{ij}^t$. The term $s_{X_{ij}^t}$ is an estimation of the standard deviation of $X_{ij}^t$, and the safety factor used is $z = 2.0$ (service level of 97.72%) , according to Chatfield *et al.* (2004). To update the $S_{ij}^t$ level, a node $j$ in stage $i$ can access to the demand data from previous periods (used to forecast the expected demand at time period $t$, $\bar{D}_{ij}^t$, and its variance, $s_{D_{ij}^t}^2$), and to the lead time data from previous periods (used to forecast the expected lead time at time period $t$, $\bar{L}_{ij}^t$), and finally uses this information to generate forecasts of lead-time demand mean $\bar{X}_{ij}^t$ and variance $s_{X_{ij}^t}^2$, as indicated in (6.3) and (6.4), respectively:

$$\bar{X}_{ij}^t = \left(\bar{L}_{ij}^t + R\right)\bar{D}_{ij}^t \tag{6.3}$$

$$s_{X_{ij}^t}^2 = (\bar{L}_{ij}^t + R)s_{D_{ij}^t}^2 \tag{6.4}$$

To estimate $(\bar{D}_{ij}^t, s_{D_{ij}^t}^2)$, according to Chatfield *et al.* (2004), each node uses a $p$-period moving averages ($NPMA(p)$) and a $p$-period moving variances ($NPMV(p)$) with $p=15$. To estimate $(\bar{L}_{ij}^t)$, each node uses running averages, which utilizes data available from all previous periods.

- **Reverse Logistic**. With the exception of the customers, all SCN nodes are allowed to return goods. Thus, replenishment order sizes may be negative.

- **Scope of Information**. Each node's SCN knowledge-base is derived from the incoming demand flow coming from the downstream partners and the outgoing flow of orders being placed with the upstream partner.

- **Timing of Actions**. In each time period, each node (in a sequence from downstream stages to upstream stages, and randomly for nodes in the same stage) performs the following sequence of actions:

   1. Update the OUT level ($S_{ij}^t$) using the forecast calculated in the previous period.

2.  Place an order $O_{ij}^t$ to raise or lower the inventory position to the $S_{ij}^t$ level.

3.  Receive products from the upstream node.

4.  Receive new orders $D_{ij}^t$ from the downstream nodes and satisfies demand.

5.  Calculate a new forecast to be used in the next period.

## 6.3. EXPERIMENTS DESIGN

Chatfield *et al*. (2004) analyze the impact of stochastic lead times, information quality and information sharing on the performance of SCNs, carrying out a factorial experiment utilizing these three indicators. For the comparison between the serial and the divergent SCNs, the following values of these factors are taken from their factorial experiment: lead time coefficient of variation $c.v. = 0.50$; no information sharing; quality of information utilized for updating the $S$ level shown in equations (6.3) and (6.4) (named IQL1 by Chatfield *et al*., 2004). These factors remain fixed in the experiments.
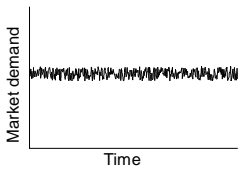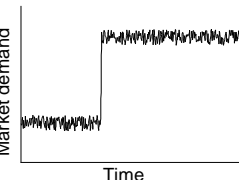
For the BWE analysis, the framework proposed by Towill *et al*. (2007) is adopted (see Chapter 2). Attending to the variance lens perspective, the demand pattern is the same as in Chatfield *et al*. (2004), i.e. demands follows a $N(50, 20^2)$ distribution. Attending to the shock lens perspective, a $N(50, 20^2)$ distribution is used, which suffer an average increment of 100% in the middle of the simulation time (not considering the warm-up period, see below), turning into a $N(100, 20^2)$. These demand patterns are applied to the only customer in the serial SCN, and to every customer in the divergent SCN.

A set of two experiments is designed: the stationary response set and the dynamic response set. In the stationary response set, in order to compare the performance of the serial and the divergent SCNs under both lenses, a global measure of $\Phi$ and *BwSl* are obtained for both demand patterns. In the dynamic set, the temporal evolution of $\Phi$ is obtained under the shock lens in order to analyze the impulse response of both SCNs in detail.

In the first set of experiments, a simulation experiment has been carried out for each SCN and for each demand pattern. Following the simulation procedure indicated in
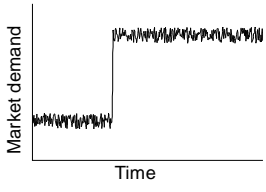
Chatfield *et al*. (2004), each experiment consists in 30 replications of 700 periods, with the first 200 periods of each replication removed as a warm-up used to set up the system. The results obtained from the replications are averaged for each experiment. To be able to compare the experiments under both lenses, metrics are calculated in the same simulation period, after the impulse time ($t$=450). The first set of experiments is summarized in Table 6.1.

**Table 6.1.** Stationary response set of experiments.

| BWE Lens | Demand Pattern | Structure of the SCN | Metrics |
|---|---|---|---|
| Variance Lens<br><br>*Market demand* vs *Time* | $N(50, 20^2)$<br>$t \in$ [0-700] | Serial SCN | |
| | | Divergent SCN | $\Phi$<br>$BwSl$<br>$t \in$ [450-700] |
| Shock Lens<br><br>*Market demand* vs *Time* | $N(50, 20^2)$ $t \in$ [0-449]<br>$N(100, 20^2)$ $t \in$ [450-700] | Serial SCN | |
| | | Divergent SCN | |

In the second set of experiments, in order to obtain the temporal response, each SCN is evaluated in different simulation periods. In the first observation, named *T*0, SCNs are simulated until the simulation time is just before the demand impulse occurs, obtaining the initial $\Phi$. Then, $\Phi$ is measured in a sequence of experiments where the simulation time starts at the demand impulse instant and the simulation time is increasing in intervals of 25 or 50 periods until the end of the original simulation time is reached ($t$=700), resulting in the experiments *T*1-*T*6. As for the first set, each experiment consists in 30 replicates, and the results obtained are averaged. This set of experiments is summarized in Table 6.2.

**Table 6.2.** Dynamic response set of experiments.

| BWE Lens | Demand Pattern | Simulation Periods | Structure of the SCN | Metrics |
|---|---|---|---|---|
| Shock Lens  | $N(50, 20^2)$ $t \in [0\text{-}449]$ $N(100, 20^2)$ $t \in [450\text{-}700]$ | $T0$: [200-449] | Serial/Divergent | $\Phi$ |
| | | $T1$: [450-475] | Serial/Divergent | |
| | | $T2$: [450-500] | Serial/Divergent | |
| | | $T3$: [450-550] | Serial/Divergent | |
| | | $T4$: [450-600] | Serial/Divergent | |
| | | $T5$: [450-650] | Serial/Divergent | |
| | | $T6$: [450-700] | Serial/Divergent | |

## 6.4. NUMERICAL RESULTS

### 6.4.1 Stationary response set

Under the variance lens, results obtained for $\Phi$ are very similar for both SCNs (see Figure 6.2), being slightly higher for the divergent SCN at the upper stages. However, under the shock lens there is an important difference between both SCNs, as $\Phi$ is considerably higher for the divergent SCN (see Figure 6.3). The average results for $\Phi$ and *BwSl,* as well as the differences between both SCNs ($\Delta(\%) = \frac{\Phi_{Divergent} - \Phi_{Serial}}{\Phi_{Serial}} * 100\%$) are shown in Table 6.3, together with the corresponding 99%-confidence intervals.
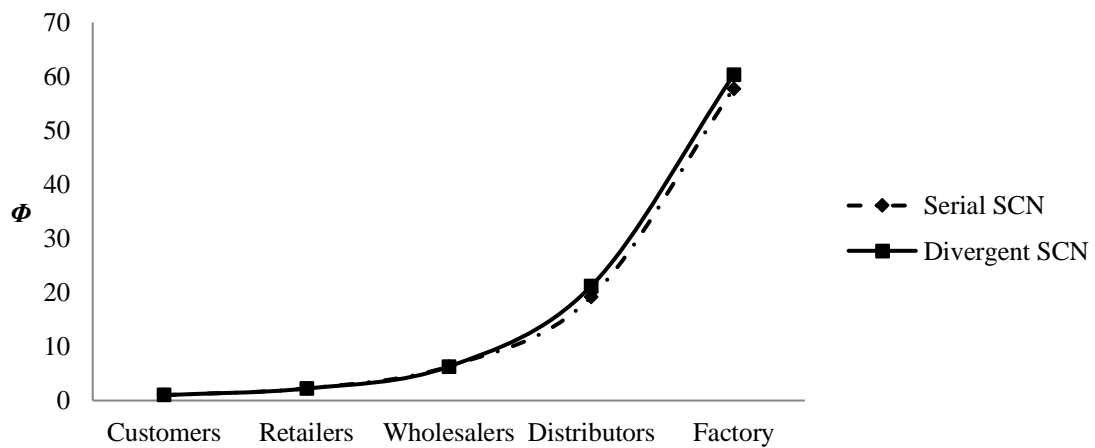


**Figure 6.2.** $\Phi$ under the Variance Lens.

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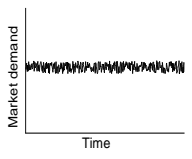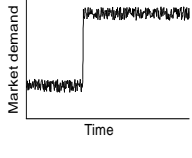
Under the variance lens, it can be seen that the values of the measures are not statistically different, which indicates a rather similar performance for both SCNS. At the lower stages, the increase of $\Phi$ is below 1%, while at the upper stages the differences are slightly higher ($\Phi$ is 5.39% higher for the divergent SCN at the distributor stage and 6.08% at the factory stage). *BwSl* helps to easily compare both SCNs. The propagation of the BWE is very similar for both SCNs, being slightly higher (6.20 %) for the divergent SCN.

**Table 6.3.** Numeric results for $\Phi$ and *BwSl*.

| Lens | SCN structure | $\Phi$ | | | | *BwSl* |
|---|---|---|---|---|---|---|
| | | **Retailer** | **Wholesaler** | **Distributor** | **Factory** | |
| Variance Lens | Serial | 2.253±0.031 | 6.329±0.177 | 19.153±0.737 | 57.766±2.667 | 13.04±0.60 |
| | Divergent | 2.258±0.029 | 6.331±0.169 | 20.186±0.763 | 61.276±2.652 | 13.85±0.60 |
| | Δ(%) | **0.222** | **0.032** | **5.393** | **6.076** | **6.20** |
| Shock Lens | Serial | 2.655±0.013 | 7.732±0.120 | 23.453±0.496 | 69.539±1.739 | 15.79±0.39 |
| | Divergent | 2.690±0.012 | 8.923±0.119 | 39.595±0.821 | 136.196±2.893 | 30.73±0.65 |
| | Δ(%) | **1.318** | **15.404** | **68.827** | **95.856** | **94.62** |
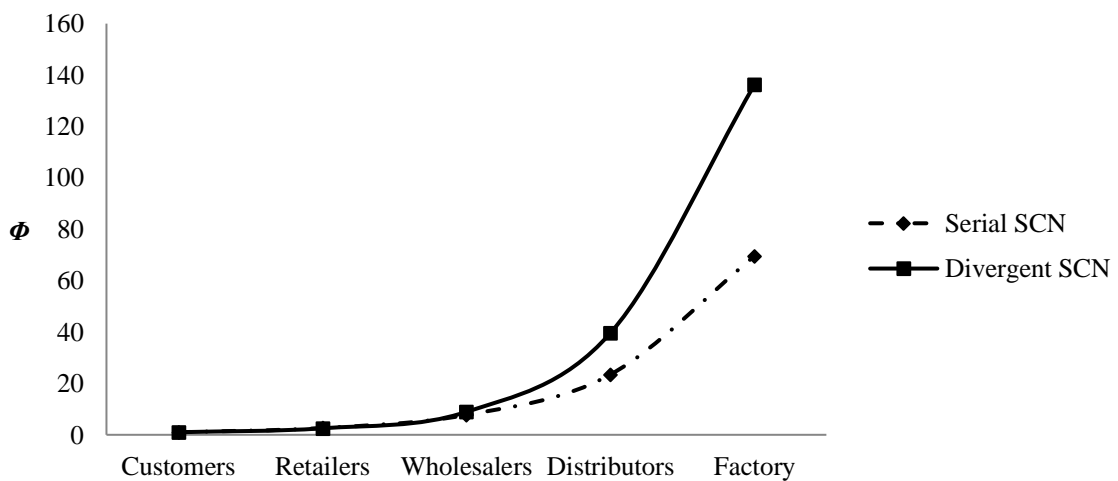


**Figure 6.3.** $\Phi$ under the Shock Lens.

66

Under the shock lens, the $\Phi$ curve is clearly stepped for the divergent SCN, with the minimum increase at the retailer stage (1.32% over the serial SCN) and the maximum increase at the factory stage (95.86% over the serial SCN). The bad performance of the divergent SCN in this case is well summarized by the value of *BwSl*, being 94.62% higher than in the serial SCN. Note that the differences in the indicators for both SCNs are statistically different, thus confirming that the divergent SCN performs worse than the serial SCN in this scenario.

### 6.4.2 Dynamic response set

Figure 6.4 shows the evolution of $\Phi$ over time for each stage after the demand impulse (rhomboids dots for the serial SCN and square dots for the divergent SCN).
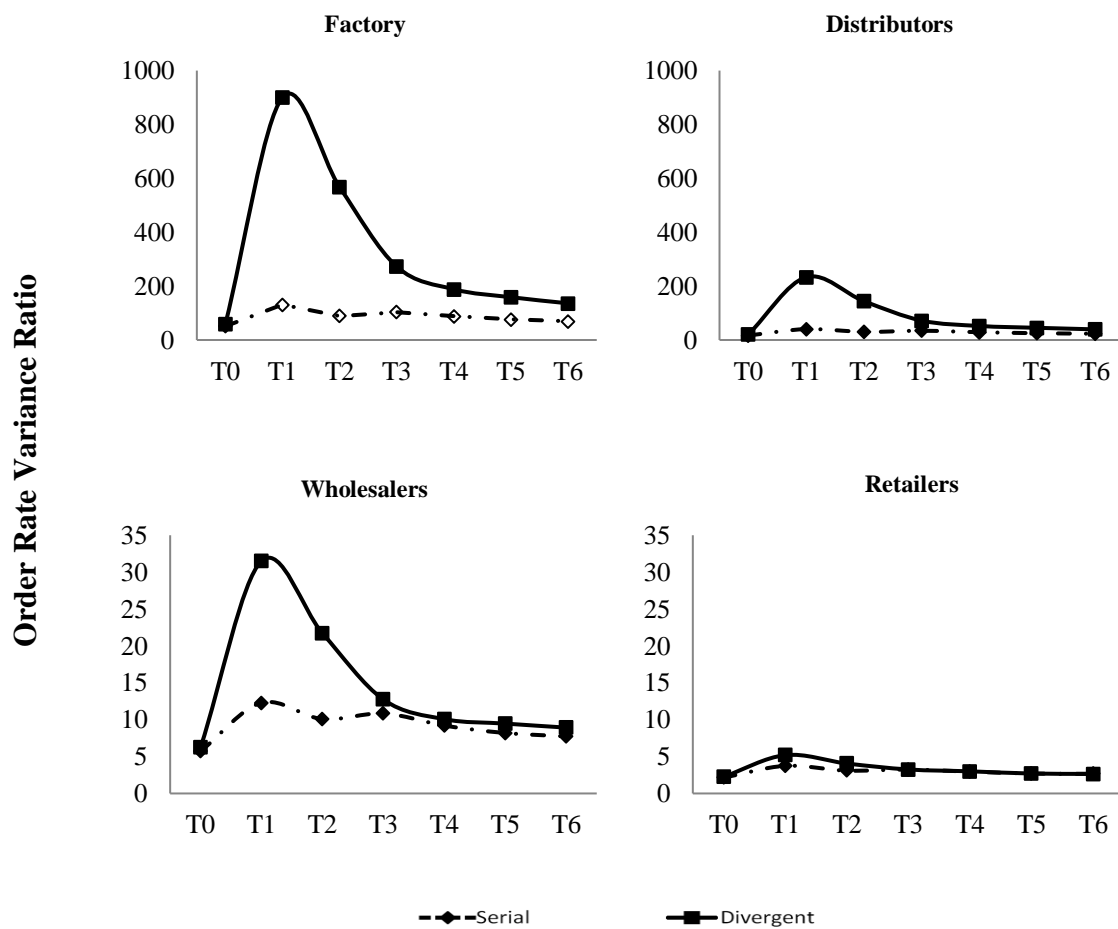


**Figure 6.4.** Evolution of $\Phi$ over time under the Shock Lens.

The differences for $\Phi$ observed between both SCNs in Figure 6.4 are plotted in Figure 6.5, showing the temporal evolution of $\Delta(\%)$ for each stage.
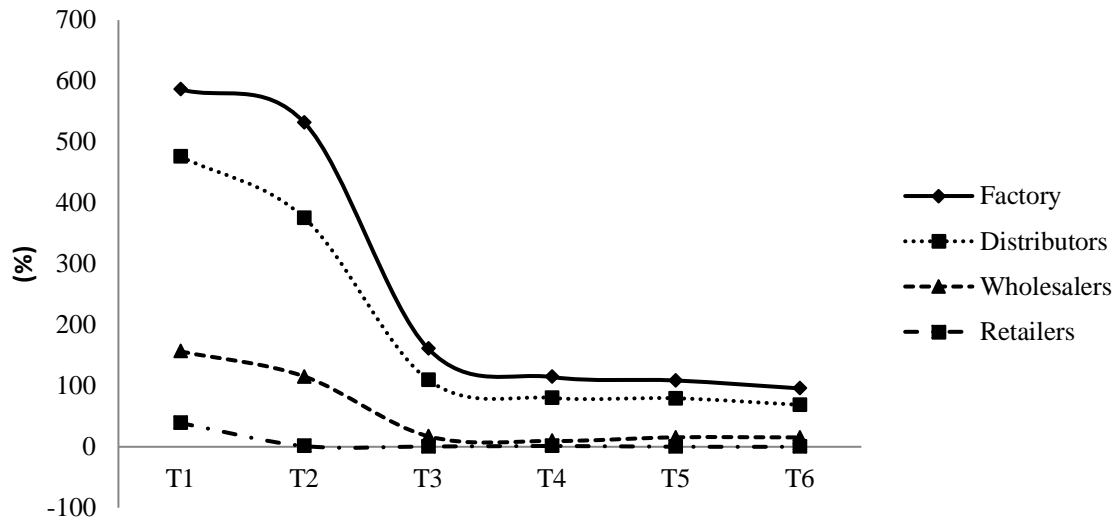


**Figure 6.5.** Divergent SCN $\Phi$ increments over the serial SCN.

From the above results it can be noted that, under an unexpected impulse in demand average:

- Both SCNs react by: 1) immediately incrementing their order variances in all stages, and 2) decreasing their order variances over time.

- The highest increase in $\Phi$ takes place just after the demand impulse ($T1$). The difference between both SCNs is maximal at this point, being higher as we move upstream (see Figure 6.5).

- The shock recovery is similar for both SCNs at the lower stages (retailers and wholesalers), whereas $\Delta(\%)$ is near to zero after $T3$ (see Figure 6.5). However, at the upper stages (distributors and factory), shock recovery is slower for the divergent SCN, obtaining high values of $\Delta(\%)$ until the end of the simulation time ($T6$).

In Figure 6.6, the order pattern at the factory stage is plotted against the customer order pattern for both SCNs under the shock lens. It is easy to see the high overreaction of the divergent SCN when the demand impulse occurs.
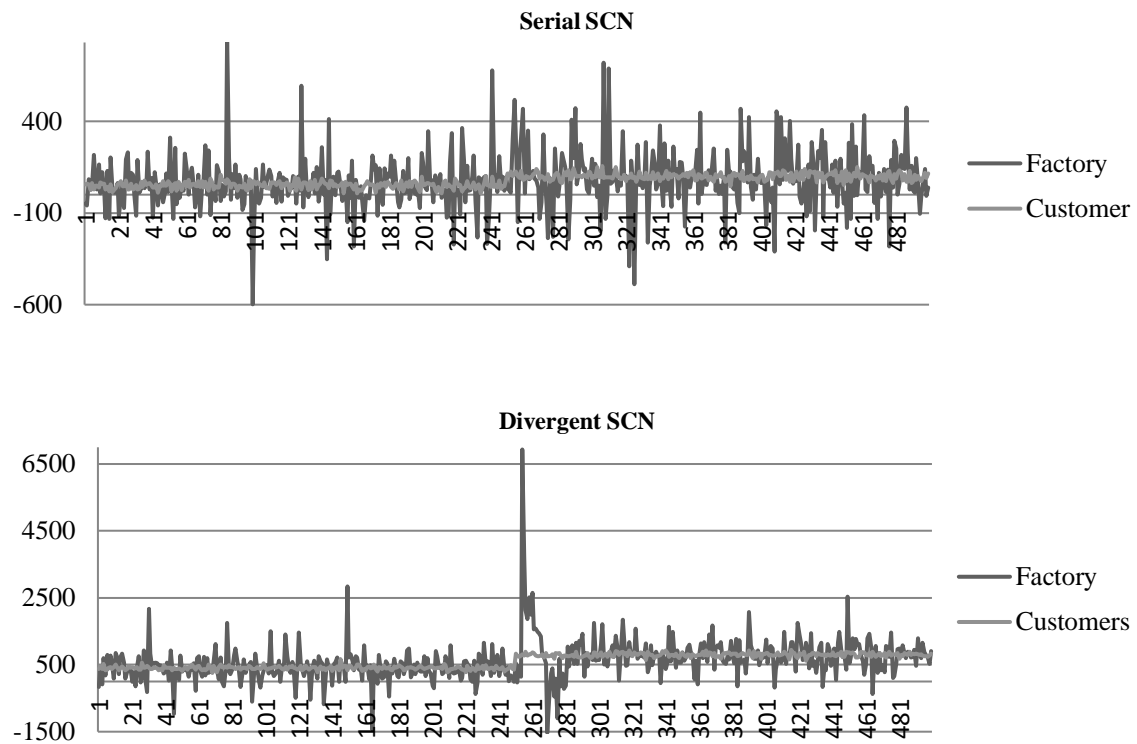
**Figure 6.6.** Factory vs end customer demand order patterns under the shock lens.

Finally, a sensitivity analysis has been performed by systematically increasing the level of end customer standard deviation in the shock lens part of the simulation. The results show that as the impulse in customer demand variability increases, standard deviation of the orders placed in the lower echelons does not increase at the same rate. For example, 47.49% increase in customer demand standard deviation in the shock lens, resulted a 25.96% increase in the standard deviation of the factory orders. In other words, the increase in the shock was transmitted in lower proportions towards the upstream levels of the SCN.

## 6.5. FINDINGS AND MANAGERIAL IMPLICATIONS

The results obtained in the previous section give new insights on the BWE research topic, considering two different lenses for the comparison of two different SCN structures. Under the variance lens, the following comments can be done:

- The BWE found in the serial and the divergent SCNs are very similar. When the demand is predictable and the nodes can adequately adjust their inventory levels

to fulfill the demand with a high customer service level, both SCNs are quasi-equivalents. A node at the stage $i$ of the divergent SCN causes the same amplification of orders that a node in the same stage $i$ of the serial SCN, because they have the same OUT and forecast policies. The orders received by each node are proportional to the end customer demand, and hence, to the amplification of orders caused by them. As the variance of orders in each stage is rated to the end customer demand variance, each stage produces similar values of $\Phi$ for both SCNs.

- The small increase observed in $\Phi$ for the divergent SCN in Figure 6.2 is caused by eventual excess of stock or by eventual stock-outs. Due to the uncertainties in the end customer demand and lead times, sometimes either the demand received may be different than the demand forecasted in the previous period, or the orders arrive earlier or later than expected, causing this phenomenon. In these cases, where the inventory level is far from the desired OUT level, a node reacts by ordering a big quantity of products (a positive order in case of stock-out and a negative order in case of excess of inventory). These exceptionally high orders are amplified upstream, increasing the variance ratio mainly in the upper stages. In view of the fact that for each node there is a certain probability that this phenomenon occurs, and that the divergent SCN has a higher number of nodes in each stage (higher vertical complexity), it happens more frequently in the divergent SCN, causing the little increment in the values of $\Phi$ at the upper stages (distributor and factory). As a summary, it can be concluded that the divergent SCN has almost the same performance in terms of BWE than the serial SCN when the end customer demand does not suffer important changes.

Using the shock lens, the following comments can be done:

- Under the shock lens both SCNs are stress tested. The end customer demand impulse causes a massive stock-out situation at the retailer stage, which is then propagated and amplified along the SCN, causing stock-outs in all the stages of the SCNs. While the factory in the serial SCN has to manage the instability caused by the stock-out of one retailer, the same factory in the divergent SCN has to manage it with the stock-outs of eight retailers. The disproportional orders of the factory and distributors in the divergent SCN can be observed in Figure

6.6, and are the cause of: the excess of variance observed in Figure 6.3, the high peaks of variances, and the slow recovery observed in Figure 6.4.

- The divergent SCN has a bad performance as compared to the serial SCN under important unpredicted changes in demand tendencies. Thus, it can be concluded that divergent SCNs are less robust than serial SCNs.

It is worth mentioning the relevance of the framework for the analysis of the BWE proposed by Towill *et al.* (2007). The authors stated that "the detection of BWE depends on which lens is used", and they proposed three different lenses for BWE analysis (variance, shock and filter lens). The experiments have shown different behaviors depending on the lens used: while for the classical variance lens analysis (stationary stochastic demand input) the BWE is similar for both SCNs, the shock lens analysis (step demand input) reveals that the divergent SCN performs worse than the serial SCN.

With respect to the managerial implications of the study, to face up with the less robustness of divergent SCNs, managers may find useful to consider the following:

- Under a shock in end customer demand, the BWE increases when the SCN structure becomes more complex as the number of echelons increases, or as the number of successors at each echelon increases. Thus, to mitigate this incremental BWE, a firm could consider simplifying the SCN structure by reducing the number of echelons or by reducing the number of successors (Sodhi and Tang, 2011). This is particularly important for SCNs characterized by high variations in the end customer demand. On the contrary, traditional arborescent SCNs opeaing in markets characterized by a stable consumer demand are less prone to the detrimental consequences of the demand amplification phenomenon.

- An adequate forecast method adjusted to the end customer demand would prevent the firm from eventual excess of stock or from stock-outs. Therefore, it is important to make an effort to implement techniques in order to better understand the end customer demand tendencies (i.e. surveys) and to anticipate important changes.

- The implementation of well-known techniques for reducing the BWE (i.e. information sharing) is highly desirable. These techniques may help managers to

have a better control of the BWE in case of important changes in the end customer demand that cannot be anticipated by the above techniques. However, it has yet to be proved how these techniques (usually tested in serial SCNs) perform in non-serial SCNs.

## 6.6 SUMMARY AND CONCLUSIONS

The literature review on Chapter 2 has revealed a lack of research on the BWE topic when the structure of the SCN is different than a serial SCN. However, real SCNs rarely adopt a traditional serial structure, often following a more complex topology. The work presented in this chapter is an attempt to cover this research gap by analyzing the BWE in a divergent SCN and by comparing its performance with those of a serial SCN already analyzed in the literature by several authors. The BWE has been observed both from a static and a dynamic perspective, being measured at the node level by the Order Rate Variance Ratio, and at the network level by the Bullwhip Slope.

The main result obtained show that divergent SCNs are more sensitive to unexpected violent changes in demand signal than serial SCNs. Two situations have been considered:

- Variance lens, i.e. stationary demand signal. In this case the performance of both SCNs is very similar, being just a little worse for divergent SCNs.
- Shock lens, i.e. demand signal suffers an unexpected violent change. In this case the performance of the divergent SCN is much worse than that of the serial SCN, showing higher variance of orders and taking more time for recovery, incurring in higher costs.

As it was pointed out in the previous section 6.5, the less robust structure of the divergent SCN might be compensated by a good information system in order to share end customer demand (information sharing) or applying smoothing replenishment orders, allowing a faster and proportional response to violent changes in the end customer demand. Such information system and smoothing replenishment are adapted to a divergent SCN in Chapter 7, testing its efficiency in this SCN configuration.

Bhattacharya and Bandyopadhyay (2011) indicated that there are operational and behavioral causes of the BWE, and that the root of all the causes is the lack of

coordination among the SCN members. In this chapter it has been shown that, in addition to the number of stages, there are also other structural factors that amplify the BWE caused by those operational and behavioral factors. The identification of these factors and a quantification of their effects are addressed in Chapter 8.

Finally, the different performance observed between the traditional serial SCN model and a divergent SCN model with higher number of companies and higher interconnection confirms the need of increasing the complexity of the SCN models in order to obtain more accurate insights on the dynamics of modern SCNs (see Chapter 2).

# Chapter 7: On bullwhip limiting strategies in divergent SCNs

## 7.1. INTRODUCTION

In Chapter 6, the differences between the dynamic of a serial SCN and a divergent SCN have been analyzed: the divergent SCN performs worse than the serial SCN (in terms of BWE) in case of a shock in the end customer demand. In order to extent the results of the previous chapter and motivated by the lack of studies on analyzing the performance of BWE limiting strategies on divergent SCNs (see Chapter 2), the aim of this chapter is twofold: (1) to analyze the impact of two well-known BWE reduction strategies such as the information sharing and the smoothing replenishment rule on a divergent SCN and (2) to compare this impact with the effect of these techniques on the widely used serial SCN.

To fulfill these research objectives the same two SCNs described in Chapter 6 are used: a four-echelon serial SCN and a four-echelon divergent SCN. Then a comparative analysis is performed between these two SCNs for four scenarios, i.e. (1) classical OUT, no info-sharing; (2) smoothing replenishment rule, no info-sharing; (3) classical OUT, info-sharing; (4) smoothing replenishment rule, info-sharing. The shock lens input demand is adopted to analyze the BWE, as described in Towill *et al.* (2007) (see Chapter 2).

## 7.2. SIMULATED SCENARIOS

Each of the simulated scenarios benchmarks the serial SCN against the divergent SCN in one of the above-mentioned cases, each of them modeling a different combination of BWE limiting strategies. These scenarios are described next:

### 7.2.1. Traditional SCN with classical OUT policy

The traditional SCN under OUT policies is arguably the most studied SCN configuration in BWE literature. Each level in the SCN issues production orders and

replenishes stock without considering the situation at either up- or downstream tiers of the SCN. Each member generates an independent production–distribution plan on the basis of incoming orders from the direct customer (Holweg and Disney, 2005). Thus, retailers forecast the customer demand on the basis of market consumption, while the up-stream echelons only take into account for their replenishment downstream incoming orders (equation (7.2)) in the risk period (Zhou *et al.*, 2010). In this scenario, the order $O_{ij}^t$ (equation (7.1)) is generated to recover entirely the gap between the OUT level and the inventory position (Cannella *et al.*, 2011). More specifically, the OUT level $S_{ij}^t$ (equation 7.3) equals the expected demand during the risk period (equation 7.4) and a safety stock to cover higher than expected demands during the same risk period (equation 7.5). The risk period is equal to the forecasted lead time ($\bar{L}_{ij}^t$) plus the review period $R$ (Disney and Lambrecht, 2008). As suggested by these authors, the inventory position of a node $j$ in the stage $i$ (equation 7.6) equals the net stock ($NS_{ij}^t$) plus the inventory on order but not yet arrived or work in progress ($WIP_{ij}^t$). The net stock equals inventory at hand minus backlog.

$$O_{ij}^t = S_{ij}^t - inventory\ position \tag{7.1}$$

$$X_{ij}^t = \sum_{k=0}^{L+R} D_{ij}^{t+k} \tag{7.2}$$

$$S_{ij}^t = \bar{X}_{ij}^t + zs_{X_{ij}^t} \tag{7.3}$$

$$\bar{X}_{ij}^t = \left(\bar{L}_{ij}^t + R\right)\bar{D}_{ij}^t \tag{7.4}$$

$$s_{X_{ij}^t}^2 = \left(\bar{L}_{ij}^t + R\right)s_{D_{ij}^t}^2 \tag{7.5}$$

$$inventory\ position = NS_{ij}^t + WIP_{ij}^t \tag{7.6}$$

### 7.2.2. Traditional SCN with smoothing replenishment rule

Similarly to the previous scenario, the information flow consists in the transmission of members' orders upstream. However, in this case, each member generates in every

review period $R$ an order quantity to recover only a fraction of the gap between the OUT level and the inventory position (Cannella and Ciancimino, 2010). In order to implement the smoothing replenishment rule the OUT formulae has to be derived in equation (7.1). Thus, order $O_{ij}^t$ can be expressed as follows:

$$O_{ij}^t = \left(\bar{L}_{ij}^t + R\right)\bar{D}_{ij}^t + z\sqrt{\left(\bar{L}_{ij}^t + R\right)s_{D_{ij}^t}^2} - NS_{ij}^t - WIP_{ij}^t \qquad (7.7)$$

The amount of the gap to recover is regulated by the decision parameters $\beta$ and $\gamma$, known as proportional controllers (Disney *et al.*, 2007). These parameters enable to alter the dynamic behavior of the SCN (Disney and Lambrecht, 2008):

$$O_{ij}^t = R\bar{D}_{ij}^t + \beta_{ij}\left(z\sqrt{\left(\bar{L}_{ij}^t + R\right)s_{D_{ij}^t}^2} - NS_{ij}^t\right) + \gamma_{ij}\left(\bar{L}_{ij}^t\bar{D}_{ij}^t - WIP_{ij}^t\right) \qquad (7.8)$$

It can be noted from equation (7.8) that the order quantity $O_{ij}^t$ is the sum of tree components: (1) a forecast on the order from the subsequent echelons, (2) a smoothed inventory gap, and (3) a smoothed work in progress gap.

### 7.2.3. Information sharing SCN with classical OUT policy

In this scenario, the information flow consists of the transmission of members' orders upstream and of the sharing of market demand (end-customer demand). Thus, a generic echelon generates the order quantity not only on the basis of the incoming orders from the direct customers, but also on the basis of market demand. Hence, unlike the traditional SCN, all members compute the OUT level and orders by considering the end-customer demand (equations (7.9), (7.10), (7.11) and (7.12)). For the serial SCN it is assumed that the end-customer demand is equal for all members. On the contrary, in the divergent SCN, the end-customer demand used by a generic echelon has to be related to its specific position in the chain. More specifically, a generic node (*i,j*) has to consider the orders placed by all the customers that are linked to this specific node as

the market demand. A node $(i,j)$ is linked to a customer $(C,j)$ if the former can trace a path through linked downstream partners to the latter. Herein, this information is defined "shared demand", and for a node $(i,j)$ it is computed as the sum of the shared demand of its downstream linked partners $(j=p)$ (equation 7.11). For instance, in the presented divergent SCN model, the shared demand for Wholesaler 1 is $ShD_{31}^t = ShD_{41}^t + ShD_{42}^t = D_{C1} + D_{C2}$.

$$\bar{X}_{ij}^t = \left(\bar{L}_{ij}^t + R\right)ShD_{ij}^t \tag{7.9}$$

$$s_{X_{ij}^t}^2 = \left(\bar{L}_{ij}^t + R\right)s_{ShD_{ij}^t}^2 \tag{7.10}$$

$$ShD_{ij}^t = \sum_{j=p} ShD_{i+1,j}^t \tag{7.11}$$

$$O_{ij}^t = \left(\bar{L}_{ij}^t + R\right)ShD_{ij}^t + z\sqrt{\left(\bar{L}_{ij}^t + R\right)s_{ShD_{ij}^t}^2} - NS_{ij}^t - WIP_{ij}^t \tag{7.12}$$

### 7.2.4. Information sharing SCN with smoothing order policy

In this scenario the information sharing and the smoothing replenishment rule are adopted simultaneously (equation (7.13)). Thus, according to the mathematical derivation of the smoothed order pattern presented before, equation (7.8) is modified by adding the "shared demand" (equation (7.11)), obtaining the following order policy:

$$O_{ij}^t = ShD_{ij}^t R + \beta_{ij}\left(z\sqrt{\left(\bar{L}_{ij}^t + R\right)s_{ShD_{ij}^t}^2} - NS_{ij}^t\right) + \gamma_{ij}\left(ShD_{ij}^t \bar{L}_{ij}^t - WIP_{ij}^t\right) \tag{7.13}$$
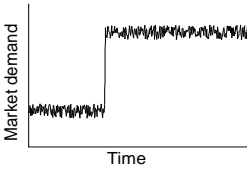
### 7.3. EXPERIMENTS DESIGN

For the BWE analysis, the shock lens perspective proposed by Towill *et al.* (2007) is adopted (see Chapter 2). The initial demand pattern is the same as in Chatfield *et al.* (2004): a $N(50, 20^2)$. According to the shock lens perspective, it suffers an increment of 100% in average at the middle of the simulation time (not considering the warm-up

period, see below), turning into a $N(100, 20^2)$. This demand pattern is applied to the only customer the in serial SCN and to every customer in the divergent SCN.

In order to tune the proportional controller, the design proposed by Disney and Towill (2006) is adopted. More specifically, the experimental level of the two parameters are related to lead time according to the following relation: $1/\beta_{ij} = 1/\gamma_{ij} = \bar{L}_{ij}^t + R$. This design has been tested by several simulations and analytical environments and it presents an extremely well-behaved dynamic response (Disney and Towill, 2006). Other parameters of the SCNs are set as in Chatfield *et al.* (2004), i.e.: review period $R = 1$, safety factor $z = 2$, $p$-period $p = 15$, lead time is assumed to be gamma-distributed with mean 4 time units for all nodes in the SCN and 0 for customers, with a coefficient of variation $c.v. = 0.50$.

Following the simulation procedure indicated in Chatfield *et al.* (2004), each experiment consists in 30 replications of 700 periods, with the first 200 periods of each replication removed as a warm-up used to set up the system. The results obtained from the replications are averaged for each experiment. The metrics used are the same as in the previous Chapter 6 (*Φ*,*BwSl*), being calculated after the impulse time (*t*=450). In Table 7.1 a summary of all sets of experiments is reported.

**Table 7.1.** Summary of experiments.

| Demand Pattern | Structure of the SCN | Order Policy | Metrics |
|---|---|---|---|
|  $N(50, 20^2)\ t \in$ [0-449] $N(100, 20^2)\ t \in$ [450-700] | Serial SCN | Traditional OUT | $\Phi$ $BwSl$ $t \in$ [450-700] |
| | | OUT + Smoothing | |
| | | OUT + Information Sharing | |
| | | OUT + Smoothing + Information Sharing | |
| | Divergent SCN | Traditional OUT | |
| | | OUT + Smoothing | |
| | | OUT + Information Sharing | |
| | | OUT + Smoothing + Information Sharing | |

## 7.4. RESULTS AND DISCUSSION

The numerical output of the experiments is presented. Data are collected and metrics are herein used to assess performance of the SCNs. In order to contrast the scenarios, the Order Rate Variance Ratio measures ($\Phi$) are plotted using the echelon position as independent variable, according to Dejonckheere *et al.*'s notation (2003a) (Figure 7.1). Discrepancies between the serial SCN and the divergent SCN are plotted in Figure 7.2. Finally, Table 7.2 reports the values of $\Phi$ by echelon (columns) and by SCN configuration (rows). Furthermore, in order to concisely compare the different scenarios, the values of the bullwhip slope are also reported in Table 7.2 for every SCN configuration and the discrepancies between the serial SCN and the divergent SCN as well. To test the statistical significance of the scenarios, the 99%-confidence interval is calculated for each one. The confidence intervals are presented next to the $\Phi$ and *BwSl* values in Table 7.2. The values obtained show that all the scenarios simulated are statistically different.
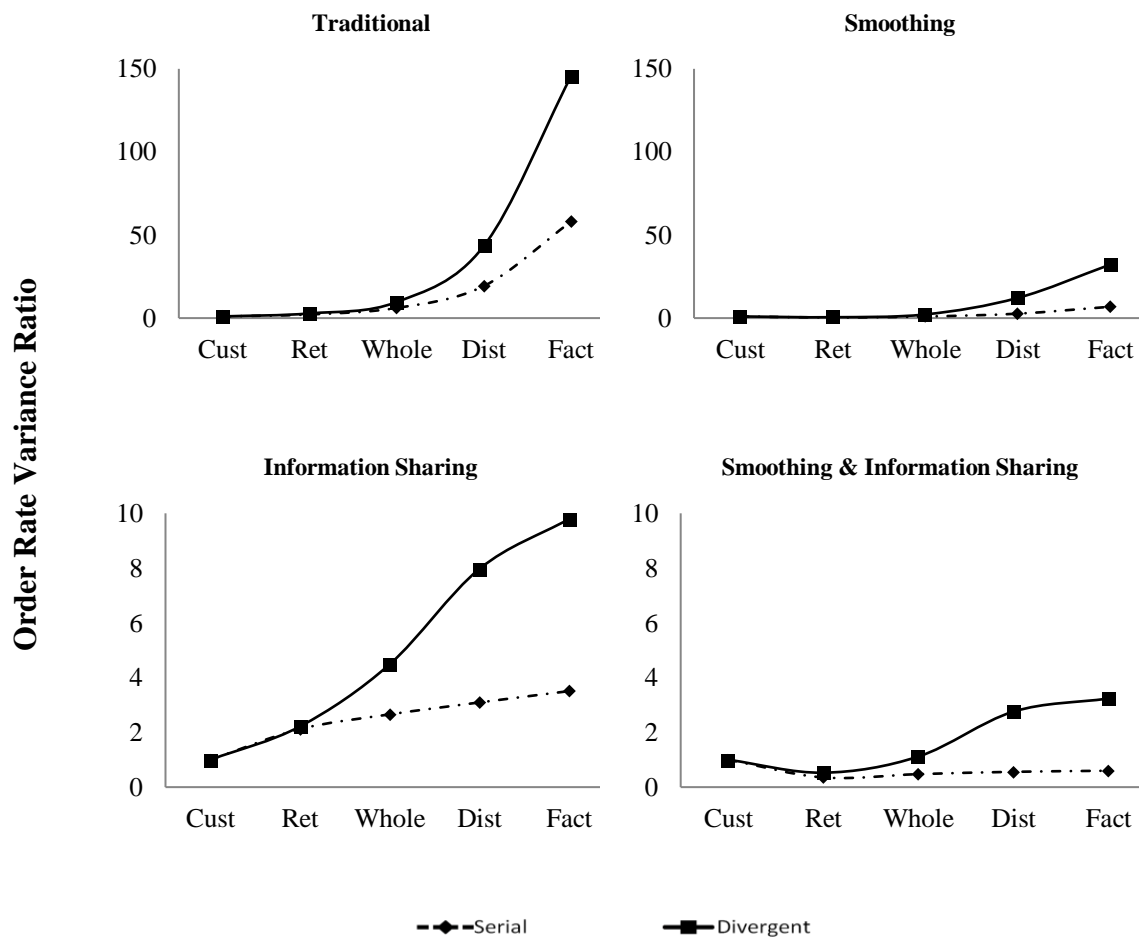


**Figure 7.1.** Order Rate Variance Ratio.
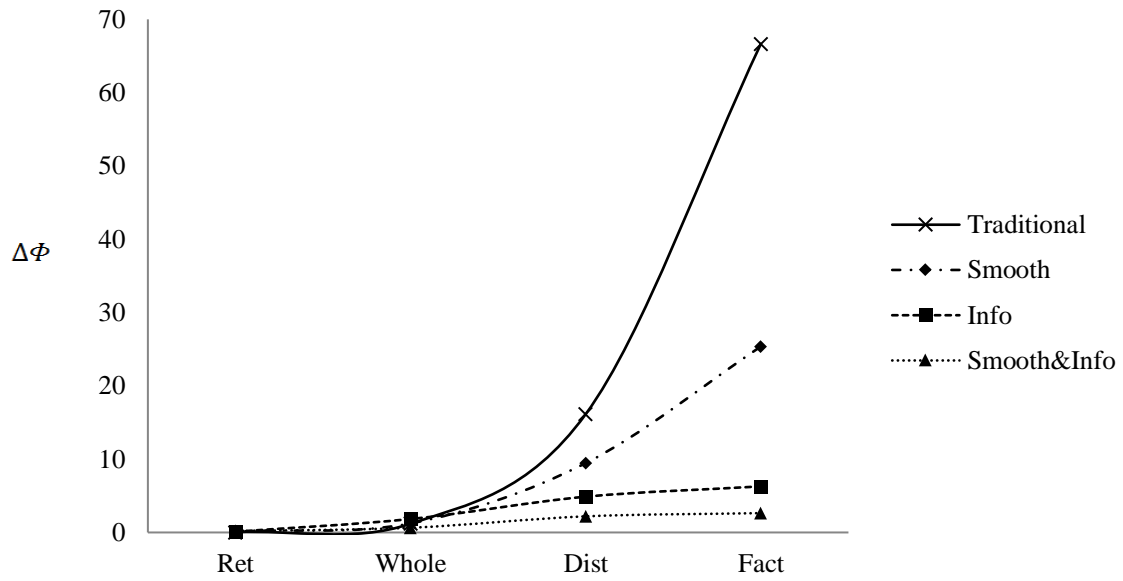
**Figure 7.2.** Order Rate Variance Ratio discrepancies between serial SCN and divergent SCN.

**Table 7.2.** Numeric results (99% confidence intervals).

| Order Policy | SCN structure | $\Phi$ | | | | $BwSl$ |
| --- | --- | --- | --- | --- | --- | --- |
| | | Retailer | Wholesaler | Distributor | Factory | |
| Traditional OUT | Serial | 2.655±0.0126 | 7.732±0.1203 | 23.453±0.4962 | 69.539±1.7386 | 15.790±0.3942 |
| | Divergent | 2.690±0.0119 | 8.923±0.1188 | 39.595±0.8211 | 136.196±2.8934 | 30.730±0.6540 |
| | $\Delta\Phi$ | **0.035** | **1.191** | **16.142** | **66.657** | **14.94** |
| OUT + Smoothing | Serial | 0.360±0.0015 | 0.957±0.0058 | 2.665±0.0221 | 6.803±0.0655 | 1.391±0.0150 |
| | Divergent | 0.530±0.0021 | 2.190±0.0246 | 12.127±0.1899 | 32.168±0.5706 | 7.393±0.1324 |
| | $\Delta\Phi$ | **0.17** | **1.233** | **9.462** | **25.365** | **6.002** |
| OUT + Information Sharing | Serial | 2.120±0.0185 | 2.657±0.0234 | 3.093±0.0299 | 3.508±0.0317 | 0.599±0.0080 |
| | Divergent | 2.219±0.0216 | 4.488±0.0399 | 7.970±0.0927 | 9.793±0.1178 | 2.334±0.0311 |
| | $\Delta\Phi$ | **0.099** | **1.831** | **4.877** | **6.285** | **1.735** |
| OUT + Smoothing + Information Sharing | Serial | 0.354±0.0017 | 0.474±0.0025 | 0.560±0.0026 | 0.599±0.0025 | -0.060±0.0007 |
| | Divergent | 0.528±0.0019 | 1.116±0.0069 | 2.756±0.0177 | 3.236±0.0192 | 0.670±0.0054 |
| | $\Delta\Phi$ | **0.174** | **0.642** | **2.196** | **2.637** | **0.73** |

### 7.4.1. Traditional SCN with classical OUT policy

The traditional scenario shows the classical exponential trend of the BWE for the serial SCN, obtaining high values of both $\Phi$ and $BwSl$. The result is in line with several studies dealing with the magnitude of BWE in a traditional SCN under the classical OUT policy (Disney and Lambrecth, 2008). Analogously, the divergent SCN shows the same exponential trend, but with higher values of $\Phi$ and $BwSl$. By analyzing the discrepancies in order variance ratio between the serial SCN and the divergent SCN, an important differentiation between both SCNs is observed, being $\Delta\Phi = 16.142$ at the distributor stage and $\Delta\Phi = 66.657$ at the factory stage. Finally, it can be appreciated how the discrepancy in the BWE propagation is equal to $\Delta BwSl = 14.94$.

### 7.4.2. Traditional SCN with smoothing replenishment rule

The smoothing scenario considerably reduces $\Phi$ and $BwSl$ for the serial SCN. In the first stages (retailers and wholesalers) there is no BWE ($\Phi \leq 1$) and then, it start to smoothly increases ($BwSl = 1.391$). As for the previous scenario, the benefits provided by the smoothing replenishment rule in term of BWE reduction are confirmed. Likewise, the divergent SCN also experiments a considerable reduction of $\Phi$ and $BwSl$, but still presents a high value of the bullwhip slope ($BwSl = 7.393$), and hence, it still shows high values of $\Phi$ at the last stages. Notice that the high discrepancies between both SCNs observed in the previous scenario have been reduced by the use of this technique.

### 7.4.3. Information sharing SCN with classical OUT policy

The reduction of $\Phi$ and $BwSl$ in the information sharing scenario is higher than in the smoothing scenario for both SCNs. As this technique uses customer demand in the calculation of orders, the first stage (retailers) shows similar values of $\Phi$ to those of the traditional scenario for both SCNs. After this stage, $\Phi$ starts to increase in a linear trend (not showing the exponential trend of the above scenarios), with a higher slope in the divergent SCN. The discrepancies between both SCNs have been considerably reduced in this scenario, being $\Delta\Phi = 6.285$ at the factory stage and $\Delta BwSl = 1.735$.

### 7.4.4. Information sharing SCN with smoothing order rule

Finally, the combination of the above techniques obtains the highest reduction of the BWE for both SCNs. At the retailer stage, similar values to those obtained in the smoothing scenario for the serial SCN are observed (information sharing does not work in this stage). After this stage, $\Phi$ starts to increase approximately in a linear trend (like the information sharing scenario), but is deterred by the smoothing factor, obtaining very low values ($\Phi \leq 1$) in all stages. The divergent SCN presents the same behavior described for the serial SCN, but with higher bullwhip slope and hence, higher values of $\Phi$. However, the discrepancy between both SCNs is very low, with $\Delta\Phi = 2.637$ at the factory stage and $\Delta BwSl = 0.73$.

### 7.5. FINDINGS AND MANAGERIAL IMPLICATIONS

The results reveal several important features of the divergent SCN and of the BWE avoidance techniques addressed in this study. First of all, the output of the simulation confirms the efficacy of the information sharing and of the smoothing replenishment rule in terms of BWE reduction in the divergent SCN. Until now this efficacy had merely been demonstrated for serial SCN models. However, the most significant results provided by this study concern the differences in term of BWE magnitude between the serial SCN and the divergent SCN. In fact, the divergent SCN configuration always performs worse than the serial SCN. However, a reduction of this discrepancy can be noted for the scenarios characterized by the implementation of one or both of the BWE avoidance techniques. Furthermore, these techniques are not only able to reduce the BWE in both SCN structures, but are even able to increase the resilience and the robustness of the divergent SCN. However, there are some differences in the impact of the information sharing and of the smoothing replenishment rule. More specifically, by adopting only the smoothing replenishment rule a significant reduction of the BWE on both SCNs can be noted, but it is still high in the last stages of the divergent SCN. With this technique, the orders placed by each node are just reduced by the smoothing factor, but are still affected by the demand pattern of the downstream nodes. When the shock in demand occurs, leading to a multiple stock-out situation occurs, the high order amplification is reduced (smoothed), but not eliminated. Furthermore, the *BwSl* is high, so a divergent SCN with high number of stages would present high values of $\Phi$. Thus,

the smoothing technique does not work properly for long divergent SCNs under a shock demand. On the contrary, information sharing performs better than the smoothing, obtaining good values of the BWE for both SCNs. The benefit of this technique is twofold: 1) nodes can adapt faster to the violent changes in market demand, and 2) the high amplification of orders due the multiple stock-out problem commented above is stopped, because nodes use the customer demand order patterns to update the base stock level instead of the order pattern of their downstream partners. Combining the benefits of the information sharing and the smoothing together, the BWE in the divergent SCN almost disappears and its propagation is very low (near zero).

From a managerial view point, a significant implication for the designing and management of SCNs has been precisely captured. In fact, till now, the unique proposed solution in scientific literature to reduce poor dynamics in divergent SCN has been the elimination of channel intermediaries (direct channel, "the Dell model") (Disney and Lambrecth, 2008). The work of Sodhi and Tang (2011), one of the few papers that have reported some insights on the differences between a serial SCN and a no-serial SCN in terms of their dynamic behavior, reveals that a firm should consider simplifying the SCN structure by reducing the number of levels or by reducing the number of successors (i.e. transforming the current SCN structure into a serial structure) to mitigate the incremental BWE. In this work, it is shown how the discrepancies between the divergent SCN and the serial SCN can be considerably reduced by an appropriate implementation of the smoothing replenishment rule and/or the information sharing (see e.g. Figure 7.2). Thus, it can be argued that information sharing and smoothing replenishment rule not only limit the BWE, even SCN characterized by more than one node in the same layer, but also are able to increase the resilience and robustness of SCNs. By reducing this incremental BWE, the differences in operation performance between the traditional structure and the divergent structure are reduced (merging their dynamic behavior) and hence, increasing the robustness of the divergent SCN without modifying its structure (suppressing nodes).

The above-mentioned result bring us to further concern about the efficient management of the SCNs. Nowadays we are not facing a temporary shock that will quickly pass, but in fact are on the verge of an "era of turbulence", that will feature higher variance in key business parameters (Christopher and Holweg, 2011). Obviously, this context exposes SCNs to tremendous shocks and impetuous alterations of the

market. Thus, the SCN crash test adopted in this work do not merely emulate the potential response of the real-world SCNs for an extreme and rare condition of the business environment. On the contrary, this response realistically represents the dynamic behavior of the real-world SCNs under the current and the advocated future business environment. In the light of the results, companies should pay more attention with respect to the past decades, when decide to reengineer and even design new SCNs. Consider the case of a company that operates with traditional control strategies and is yet able to perform well in the current market. If this company is willing to enhance their market by covering further geographical positions, probably should increase their distribution, wholesaler and retailer centers. Obviously this would amplify the complexity of the chain structure. As direct consequence, this company would risk to experiment a decrement of the whole operational performance. Thus, the potential benefit provided by the acquisition of new market share can be leveraged by a structurally decaying of the dynamic behavior. On the contrary companies adopting these BWE avoidance strategies, such as the external collaboration by information sharing strategies, pursuing the "new supply chain agenda" (see e.g. Stank *et al*., 2011), would reduce these risks and in any case would be more protected against the effect of the "era of turbulence" than the traditional SCN.


## 7.6. SUMMARY AND CONCLUSIONS

The work presented in this chapter explores the impact of some well-known BWE avoidance strategies (i.e. the smoothing replenishment rule and the information sharing) when applying on different configurations of the SCN (i.e. a serial SCN and a divergent SCN). The analysis has been carried out using the shock lens proposed by Towill *et al*. (2007), which is a stress-test related to the robustness of the system.

The results confirm that the BWE avoidance features of the strategies are also significant for the divergent SCN. Nevertheless, under these conditions, the divergent SCN performs worse than the serial SCN in all the scenarios. This bad behavior is caused by the higher complexity of the divergent SCN, which leads to a loose in robustness in relation to the serial SCN. However, the discrepancies in performance between both SCNs can be considerably reduced by the adoption of the two BWE avoidance strategies analyzed. Furthermore, it is shown how these strategies not only

reduce the BWE in SCNs, but also increase the robustness of complex SCNs, such as the divergent SCN.

The best results are offered by the combination of the smoothing replenishment rule with the information sharing. However, the discrepancies between both SCNs still persist, not being completely removed. This observation opens a new research line in developing new techniques which implicitly consider the inherent complexity of the divergent topology and attempt to totally erase the discrepancies with the serial SCN. These techniques would allow managing a divergent SCN with the same robustness than the classical serial SCN.

Finally, it is worth mentioning that the results obtained in this chapter and the results obtained in Chapter 6 confirm the existence of differences between the dynamic behavior of the serial SCN and other SCN configurations (i.e. the divergent SCN).

# Chapter 8: A systematic analysis of the structure of divergent SCNs and bullwhip

## 8.1. INTRODUCTION

In previous chapters, the divergent SCN configuration has been benchmarked against the classical serial SCN. The results reveal different dynamics behaviors in terms of BWE. In particular, under a shock in the end customer demand, the divergent SCN performs worse than the serial SCN. Furthermore, even though the effectiveness of the information sharing and the smoothing replenishment rule on reducing the BWE in the divergent SCN has been proved, this configuration still perform worse than the serial SCN. These results lead to think that the structure of the SCN may impact on the BWE. In order to confirm this hypothesis, this chapter analyzes the potential relation between the structure of the SCN and the BWE. More specifically, this chapter presents: (1) an analysis of the divergent SCN configuration in search of its structural factors, (2) a structured full factorial design of experiments in which the configuration of the SCN is systematically varied through its different structural factors, remaining the rest of the parameters fixed, (3) a statistical analysis (ANOVA) and a discussion of the results obtained for two different demand perspectives (i.e. the variance lens and the shock lens, see Chapter 2).

## 8.2. THE DIVERGENT SCN CONFIGURATION

In this section, the structural elements of a generic SCN are described, and then, the inherent characteristics/constrains of the divergent configuration are formalized. The SCN structure arises from the connected facilities that work together in order to supply products or services. In a SCN, each link represents the flow of materials and information that makes possible the functions of procurement, processing (or manufacturing), storage and distribution. For any given SCN, each functional level comprises an echelon, and there may be numerous facilities within each echelon (Beamon and Chen, 2001). This definition of the SCN structure is in accordance with the growing literature on complex networks, in which the SCN is modeled as a network by a set of "nodes" that represent autonomous business units (firms or facilities), and a

set of "connections" (links) that link these firms together in demand-supply relationships for the purposes of creating products or services (Hearnshaw and Wilson, 2013; Gerschberger *et al.*, 2012; Wen *et al.*, 2012; Kim *et al.*, 2011; Li *et al.*, 2010a; Li *et al.*, 2010b; Li *et al.*, 2009; Choi *et al.*, 2001). Hence, in line with this literature, the structure elements of a SCN are formalized as follows:

- ✓ Echelons: the number of echelons is denoted by $i \in (1, E)$, with $E$ the total number of echelons in the SCN. Echelons are numbered downstream from the suppliers, which are in echelon $i = 1$.

- ✓ Nodes: a generic node $j$ in echelon $i$ is denoted by $n_{ij}$. The number of nodes in a specific echelon $i$ is $N_i$. The total number of nodes in the SCN is: $\sum_{i=1}^{E} N_i = N$.

- ✓ Links: a link between nodes $n_{ij}$ and $n_{i'j'}$ is denoted by $l(n_{ij}, n_{i'j'})$ and the total number of links is $L$. There are two commonly used indicators to measure the degree of linkage in a SCN, namely the connection degree and the cluster coefficient (see e.g. Wen *et al.*, 2012; Kim *et al.*, 2011; Xuan *et al.*, 2011; Li *et al.*, 2010a; Barabási *et al.*, 2002) . The connection degree $D_{ij}$ is defined as the sum of a node's links (Li *et al.*, 2010a). The number of suppliers linked with node $n_{ij}$ is the in-degree ($di_{ij}$), and the number of customers linked with a node $n_{ij}$ is the out-degree ($do_{ij}$) (Kim *et al.*, 2011; Xuan *et al.*, 2011). The sum of the in-degree and the out-degree is the connection degree: $D_{ij} = di_{ij} + do_{ij}$. The clustering coefficient $C$ is the probability that two nearest neighbors of a node are also nearest neighbors of one another (Li *et al.*, 2010a). Given node $n_{ij}$ linked to $k_i$ other nodes in the system, if these $k_i$ nodes form a fully connected clique, there are $k_i(k_i - 1)/2$ links between them. Let us denote by $\lambda_i$ the number of links that connect the selected $k_i$ nodes to each other. The clustering coefficient for node $n_{ij}$ is then $2\lambda_i/k_i(k_i - 1)$ (Barabási *et al.*, 2002).

The number of nodes, the number of echelons, and the structure of the material and information flows (links) has given rise to a structural classification scheme of SCNs based on the material relationship between nodes (Beamon and Chen, 2001). Up to now, most of the existent literature on the BWE topic has analyzed the classical serial SCN. In this SCN, the number of nodes in each echelon is limited to one ($N_i = 1$), and hence, the number of nodes and echelons in the SCN is the same ($N = E$). The connection degree is also limited: each node supplies to one node in the successor

echelon ($do_{ij} = 1$) and it is supplied by one node in the predecessor echelon ($di_{ij} = 1$), thus limiting the total number of links to $L = N - 1$. Summing up, the structure of the serial SCN configuration is very restrictive: by selecting the quantity of one of the structural elements above mentioned (echelons, nodes or links), the SCN structure is defined, thus limiting the analysis of the influence of the SCN structure on the BWE to the number of echelons.

The divergent SCN configuration is less restrictive than the serial configuration. The inherent structural restrictions of divergent SCNs are described and formalized next:

1. The number of nodes in each echelon is equal or greater than the number of nodes in its predecessor, i.e.: $N_i \geq N_{i-1}$. Furthermore, in order to exclude the serial SCN, the total number of nodes is constrained to $N \geq E+1$.

2. A node $n_{ij}$ can supply to any number of nodes in the successor echelon ($do_{ij} \geq 1$), but can be supplied only by one node from the predecessor echelon ($di_{ij} = 1$) (Beamon and Chen, 2001).

3. Nodes in the same echelon are not linked. Hence, the network clustering coefficient *C* is zero. This is consistent with most cases in real-world SCNs (e.g. divergent SCN), that is, entities in the same echelons normally have no demand-supplier relations (Li *et al*., 2010a). This constraint, together with the previous restriction, limits the total number of links to the total number of nodes minus one: $L = N - 1$.

By observing the above constrains, it can be noted that *N* is greater than *E* in divergent SCNs and thus, echelons are allowed to contain more than one node. Furthermore, for a given *E*, there is no upper bound for *N*. Thereby, any distribution of nodes across the SCN satisfying restriction (1) is allowed. In addition, nodes can supply to any number of nodes downstream, as indicated by restriction (2). Hence, there might be nodes with a high connection degree while others with low connection degree, resulting in SCNs with different degree distributions. In a first attempt to measure the impact of the SCN structure on the BWE, the connection degree is not considered as a factor, and for this reason, the divergent SCNs under analysis have homogeneous degree distributions: all nodes in the same echelon have similar connection degrees. Instead, this work focuses on the number of echelons, the number of nodes, and the distribution of links (or nodes) along the SCN.

Given a SCN characterized by [*E*, *N*], there are multiple configurations depending on how nodes are distributed over the echelons. SCNs with different configurations may have different behavior in terms of BWE. To characterize the different configurations, a "divergence factor" (*divF*) is proposed, defined as the standard deviation of the number of nodes across the echelons of the SCN related to the average number of nodes in each echelon (*N/E*) (equation (8.1)). If nodes are uniformly distributed (i.e. identical number of nodes in each echelon), the SCN is characterized by a serial topology (see Figure 8.1), thus obtaining a *divF* of zero. On the contrary, a divergent SCN, with an increasing number of nodes in consecutive echelons, would present a *divF* greater than zero. Furthermore, it can be distinguished between SCNs with lower *divFs* and SCNs with higher *divFs* (see Figure 8.1). The former are SCNs with a density of nodes close to the average (*N/E*) in each echelon and thus, characterized by echelons with similar importance in the supply path to the end customers (i.e. all nodes supplies to more or less the same quantity of nodes downstream). The latter are SCNs in which the first echelons have a low density of nodes and the last echelons (retailers) have a high density of nodes. These SCNs are characterized by echelons with a critical importance in the supply path to the end customers (i.e. a few nodes supplying a high number of nodes downstream).
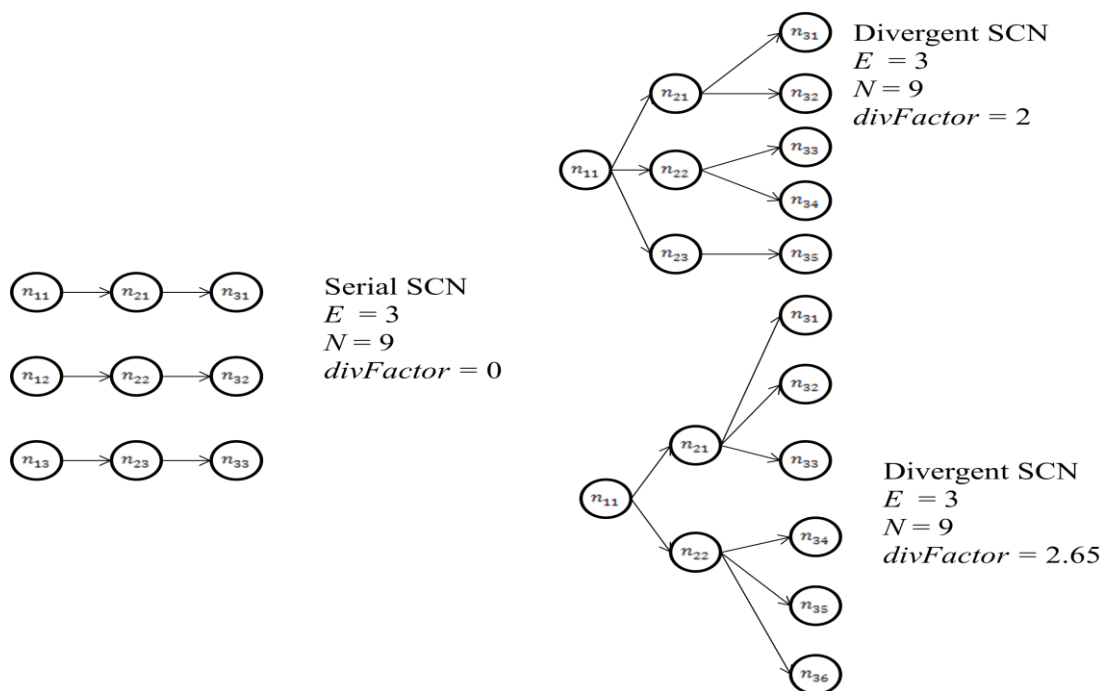


**Figure 8.1.** Three different SCNs configurations with the same *E* and *N*, and an increasing *DivF*.

$$divF = \sqrt{\sum_{i=1}^{E} \frac{(N_i - N/E)^2}{E}} \qquad (8.1)$$

## 8.3. DESIGN OF EXPERIMENTS

The SCN model used is the same described in Chapter 5, Section 2. To analyze the impact of different levels of the structural factors on the BWE a full factorial set of experiments is designed. Different levels of each factor are tested, allowing obtaining information about the main effects of each factor and its interactions with the rest of the factors and yielding conclusions that are valid over a wide range of experimental conditions.

The design of experiments chosen is summarized in Table 8.1. In order to assess the impact of the structural factors on BWE, three levels have been considered for factors $E$ and $N$ (low, medium and high), and two levels for $DivF$ (low and high). SCNs with a low value of $E$ are small SCNs with a low number of intermediaries (products require low processing and are delivered almost directly to customers, e.g. Provider, Factory, Retailer and Customer). On the contrary, SCNs with higher $E$ values are those with a high number of intermediaries (typically big distribution networks delivering products worldwide). SCNs between those levels of echelons belong to the medium level. Values of $N$ are proportional to the number of echelons. SCNs with higher $N$ values are those with a high number of companies in each level and, in the end, high number of retailers, thus having a better geographical availability to customers. On the contrary, SCNs with lower $N$ value present a low number of retailers, while those between low and high $N$ belong to the medium level. $DivF$ value is restricted for a given combination of $E$ and $N$, having a lower bound ($Min$) and an upper bound ($Max$) (see Table 8.1). Values belonging to the first half of the interval [Min, Max] correspond to the low level of $DivF$, and values belonging to the second half correspond to the high level of $DivF$.

The factorial design with these levels requires 18 observations (3x3x2). The design of experiments carried out by other authors is often limited to fixed values of each level (see e.g. Hussain *et al*., 2012; Patel and Jena, 2012; Bottani and Montanari, 2010; Paik and Bagchi, 2007; Khumwan and Pichitlamken, 2007; Chatfield *et al*., 2004). In order to obtain more general results, an interval of possible values for each level is used

instead of a fixed value (see Table 8.1). In each replication, the values for each level of the factors are chosen randomly among all possible values within the interval. The intervals for each factor have identical sizes. Due to the high variability introduced by the use of these intervals of values for each factor instead fixed values, a high number of replications (150) has been run for each combination of factors, obtaining a total of 2,700 simulation runs.

**Table 8.1.** Full Factorial Set of Experiments.

| Structure Factors | Levels and Intervals of values |
|---|---|
| $E$ | Low: $E \in [2-4]$; Medium: $E \in [5-7]$; High: $E \in [8-10]$ |
| $N$ | Low: $N \in [E - 3E]$; Medium: $N \in [3E - 6E]$; High: $N \in [6E - 9E]$ |
| $divF$ | Min: $\sqrt{\dfrac{\left(N - floor\left(\frac{N}{E}\right)*E\right)^2}{E}}$; Max: $\sqrt{\dfrac{(E-1)*(1-\frac{N}{E})^2 + (N - E + 1 - \frac{N}{E})^2}{E-1}}$; <br> Low: $divF \in \left[Min, Min + \left(\frac{Max - Min}{2}\right)\right]$; High: $divF \in \left[Min + \left(\frac{Max - Min}{2}\right), Max\right]$ |

In line with the procedure followed in previous chapters, in order to increase the robustness of the BWE analysis two different perspectives or "lenses" from the framework proposed by Towill *et al*. (2007) have been adopted (see Chapter 2). In the variance lens scenario, the demand pattern is the same as in Chatfield *et al*. (2004), i.e. demand follows a $N(50, 20^2)$ distribution. In the shock lens scenario, a $N(50, 20^2)$ distribution suffer an average increment of 100% in a certain time period (see Table 8.2), turning into a $N(100, 20^2)$. These demand patterns are applied to every customer in the SCN. A set of the above mentioned 2,700 experiments has been run using the variance lens and another identical set has been run using the shock lens, making a total of 5,400 experiments.

To isolate the effects of the structural factors on the BWE, other characteristics which are known to be BWE initiators have not been included in the SCN model, with the exception of the stochastic demand and its forecast. The selection of the parameter's values of the SCNs has been done according to Chatfield *et al*. (2004) (see Table 8.2). The simulation horizon is set to 900, with the first 400 periods used as a warm-up used to set up the system.

**Table 8.2.** Model's parameters.

| Symbol | Designation | Value |
|--------|-------------|-------|
| $P$ | Periods of forecasting | 15 |
| $Z$ | Safety factor | 2 (service level of 97.72%) |
| $R$ | Review interval | 1 |
| $L$ | Lead time | 4 |
| $simTime$ | Simulation time | 900 |
| $wUP$ | Warm-up | 400 |
| $vL$ | Variance Lens | $N(50, 20^2) \forall t$ |
| $sL$ | Shock Lens | $N(50, 20^2) \, t \in [0\text{-}549]$ $N(100, 20^2) \, t \in [550\text{-}900]$ |

The BWE has been measured by a peak of orders metric (measure the extreme swings in order patterns), which is appropriate for the shock lens scenario (Towill *et al.*, 2007). Since the dynamics of the order pattern at the first echelon presents the "worst-case" scenario, the BWE registered at this echelon is analyzed (Hussain *et al.* 2012). Hence, the BWE is measured as the maximum change in orders placed by nodes in the first echelon. Since the divergent SCN is allowed to contain more than one node per echelon, it is necessary to use an aggregate measure. Therefore, the sum of orders of every node $j$ in the echelon $i$ ($O_{ij}^t$) are considered, resulting in an aggregate order pattern for the echelon $i$: $AO_i^t = \sum_{j=1}^{n_i} O_{ij}^t$. Thus, the peak of orders in echelon one is formalized as follows:

$$PeakO_1 = \max(AO_1^t) - \min(AO_1^t) \, \forall t \in [wUP, simTime] \tag{8.2}$$

## 8.4. RESULTS AND NUMERICAL ANALYSIS

In order to identify the statistically significant factors, two ANOVAs are performed separately for the variance lens and the shock lens, and both scenarios are analyzed. The independent variables are factors *E, N,* and *DivF,* while the dependent variable is the level of order instability at the first echelon ($PeakO_1$) in the SCN.

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Systems are often driven primarily by some of the main effects and low-order interactions, say, two-factor interactions, while higher order interactions are negligible for all practical purposes (Hinkelmann and Kempthorne, 1994). Main effect refers to the effect of a structural factor on the BWE when the factor's value is changed from one level to another. Interaction refers to the effect of a particular structural factor value changing as the values of another factor change. Since high-order interactions are often minimal, only information on the main effects and low-order interactions is analyzed for each scenario. After analyzing the variance and the shock lens scenarios, a comparison between both of them is performed.

### 8.4.1. Variance Lens

ANOVA results are presented in Table 8.3, showing the degree of freedom (DOF) of each factor, $F$-ratio, $p$-value, and partial $R^2$. When all factors are considered together, the model is statistically significant with a 95% confidence level. The value of $R^2$ is 0.891, indicating that 89.1% of the variation in $PeakO_1$ can be explained by the structural factors. Furthermore, it can be seen that all structural factors are statistically significant, as well as the interaction between echelons and nodes. Figure 8.2 show the main effects of the structural factors (*E, N, DivF*) by plotting the $PeakO_1$ averages for each level of the factors (Low, Medium, High). In the subsequent analysis, all $PeakO_1$ values appear divided by $10^4$ (1E4).

**Table 8.3.** ANOVA results in Variance Lens scenario.

| Factors | DOF | $F$-ratio | $p$-value | $R^2$ (percent) |
|---|---|---|---|---|
| *Model* | *17* | *1290.495* | *<0.001* | *89.1* |
| Echelons | 2 | 10776.161 | <0.001 | 88.9 |
| Nodes | 2 | 111.484 | <0.001 | 7.7 |
| Divergence | 1 | 141.558 | <0.001 | 5.0 |
| Echelons * Nodes | 4 | 3.196 | 0.013 | 0.5 |
| Echelons * Divergence | 2 | 1.498 | 0.224 | 0.1 |
| Nodes * Divergence | 2 | 2.130 | 0.119 | 0.2 |

Looking at the main effects in Figure 8.2 and in Table 8.3, it can be noted that the most significant factor is the number of echelons: SCNs with higher number of echelons show higher BWE, following an exponential trend. This result is in line with numerous

works that already have identified this factor as one of the most influential in contributing to the BWE (Bottani and Montanari, 2010; Paik and Bagchi, 2007; Chatfield *et al.*, 2004; Disney *et al.*, 2004, among others). In fact, by adding echelons to a SCN the number of decision points increase, contributing to a higher demand distortion. Thus, each SCN member faces a more fluctuating order pattern (Paik and Bagchi, 2007). This behavior is observed in the simulation runs, and it can be noticed in Figure 8.2: SCNs with a low number of echelons show a low value of $PeakO_1$, but it abruptly increases when moving to SCNs with medium and high number of echelons.
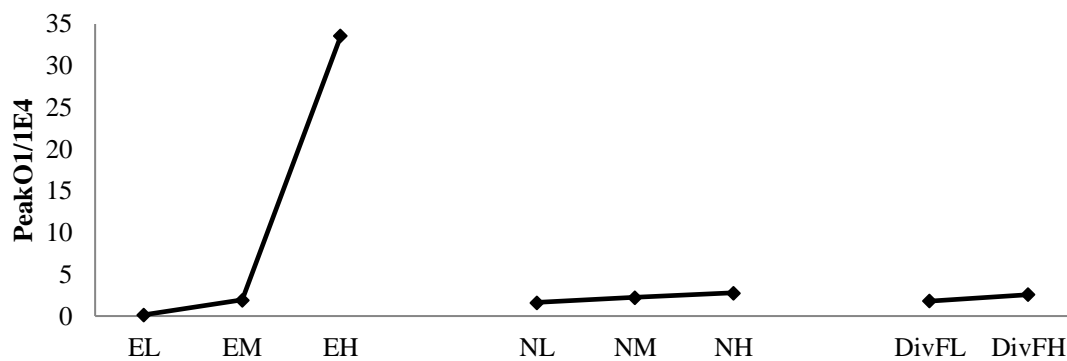


**Figure 8.2.** Main effects in Variance Lens scenario.

The number of nodes and the divergence of the SCN are both significant, but with a lesser impact on the BWE. According to Table 8.3, the number of nodes has a slightly higher impact on the BWE than the divergence of the SCN. SCNs with higher number of nodes have higher BWE, showing a linear trend. Taking into account that each node distorts the demand signal due to the inventory policies, forecast rules and lack of coordination, demand distortion is higher when increasing the number of nodes in the SCN and hence, BWE increases. More specifically, by increasing the total number of nodes in a given SCN, we are in fact increasing the number of nodes per echelon (see Figure 8.3-above). In this situation, nodes may have to fill the demand from a higher number of nodes downstream and hence, they have to face a higher variability of orders and, consequently, BWE increases.

The divergence of the SCN has the lowest impact on the BWE among the three structural factors. SCNs with higher divergence show higher BWE, following a linear trend. In a SCN with low divergence (see e.g. Figure 8.3-below), nodes are uniformly distributed along the echelons (the number of nodes per echelon ($\sum_j n_{ij}$) is close to the

average (*N/E)*). In this situation, demand is also uniformly distributed among the different nodes, thus limiting the amplification effect. However, when the divergence of the SCN increases ($\sum_j n_{ij}$ is far from *N/E*), there are one or more critical echelons in which the number of nodes abruptly increases and therefore, there a few nodes supplying a high number of nodes downstream in these echelons, as it can be seen in Figure 8.3-below. This situation increases the variability of orders received by these nodes and hence, increases the BWE.
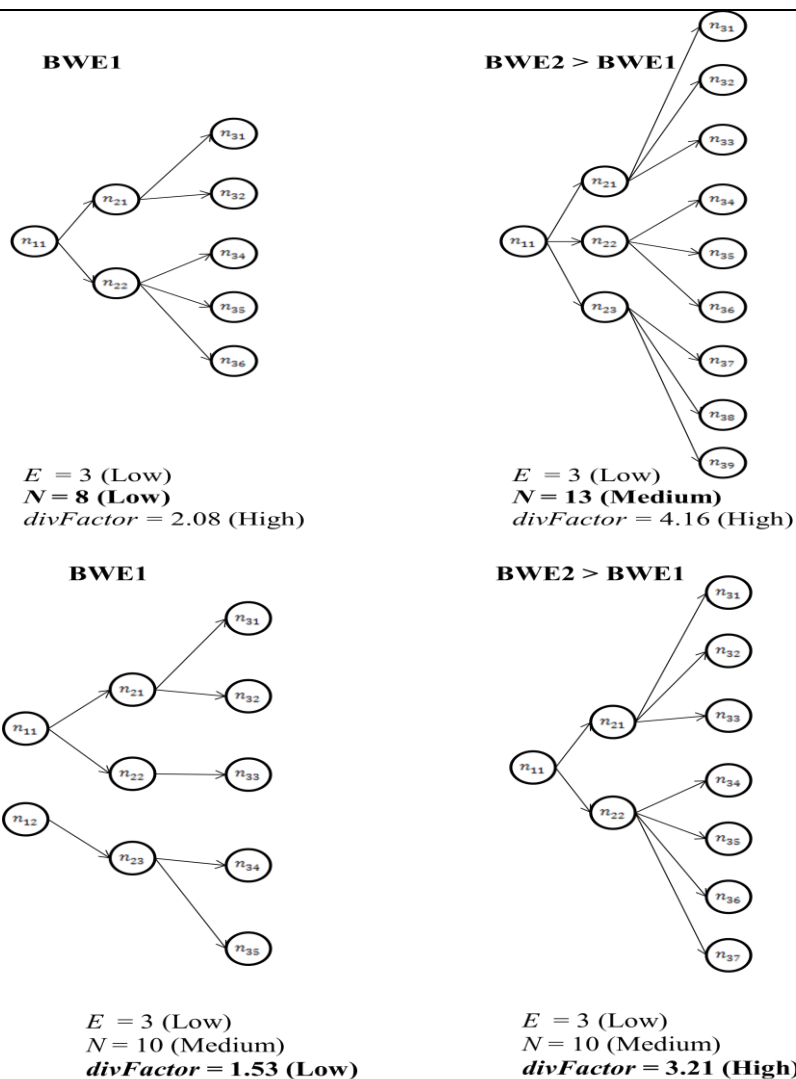


**Figure 8.3.** Increasing *N* (above) and *divF* (below) in a divergent SCN.

Finally, there is one significant interaction between the number of echelons and the number of nodes, although it has a low impact on the overall BWE. A simple but powerful "interaction plot" is used to determine the severity of the interaction between

these factors. Interaction plots are obtained by graphing the combined effects of the pairs of the factors studied. Due to the exponential nature of the obtained interaction curves, logarithms have been used to transform them into linear curves, in order to clarify its interpretation (see Figure 8.4). In fact, there is a small interaction between the number of echelons and the number of nodes, since the interaction curves are not parallel at all. More specifically, the *NH* curve has lower slope than the other curves. Hence, increasing the number of echelons in a SCN with a high number of nodes has a slightly lower impact than in SCNs with low or medium number of nodes. Another interpretation is that increasing the number of nodes results in a lower impact since the SCN has a higher number of echelons. This interpretation has been statistically contrasted by running a single-variable test (see Table 8.4). In this test, the effect of factor $N$ is contrasted for each level of factor $E$. In fact, increasing the number of nodes has a significant impact on BWE no matters the number of echelons of the SCN ($p<0.001$). However, its impact decreases as the number of echelons increases (check partial $R^2$ in Table 8.4).

**Table 8.4.** Single-variable test for the interaction between $E$ and $N$ in Variance Lens scenario.

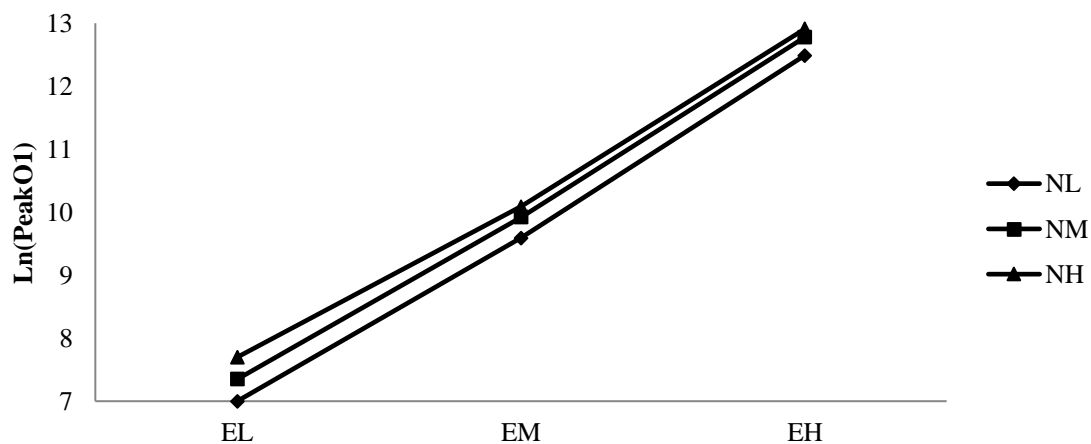| Echelons | $F$-ratio | $p$-value | $R^2$ (percent) |
|----------|-----------|-----------|-----------------|
| Low | 63.364 | <0.001 | 4.5 |
| Medium | 31.747 | <0.001 | 2.3 |
| High | 22.765 | <0.001 | 1.7 |



**Figure 8.4.** Interaction between $E$ and $N$ in Variance Lens scenario.

### 8.4.2. Shock Lens

ANOVA results are summarized in Table 8.5. When all factors are considered together, the model is statistically significant at the 95% confidence level with an overall $R^2$ of 0.892, indicating that 89.2% of the variation in $PeakO_1$ can be explained by the structural factors considered. Furthermore, all factors are found to be statistically significant, as well as two of the interactions. Figure 8.5 show the main effects of the structural factors (*E, N, D*) by plotting the $PeakO_1$ averages for each level of the factors (Low, Medium, High). As in the previous analysis, all $PeakO_1$ values appear divided by $10^4$ (1E4).

**Table 8.5.** ANOVA results in Shock Lens scenario.

| Factors | DOF | *F*-ratio | *p*-value | $R^2$ (percent) |
|---|---|---|---|---|
| *Model* | *17* | *1305.427* | *<0.001* | *89.2* |
| Echelons | 2 | 10231.880 | <0.001 | 88.4 |
| Nodes | 2 | 439.303 | <0.001 | 24.7 |
| Divergence | 1 | 693.143 | <0.001 | 20.5 |
| Echelons * Nodes | 4 | 1.877 | 0.112 | 0.3 |
| Echelons * Divergence | 2 | 65.821 | <0.001 | 4.7 |
| Nodes * Divergence | 2 | 7.909 | <0.001 | 0.6 |

In view of the main effects in Figure 8.5 and the data from Table 8.5, it is noticeable that the most significant factor on the BWE is the number of echelons: SCNs with higher number of echelons show higher BWE, following an exponential trend. The average shock in demand causes an unexpected multi stock-out at the retailer level. Nodes at this level react by placing higher orders than usual to the upstream nodes, which fall in a stock-out situation too. This effect is amplified from one echelon to another, increasing the fluctuation of orders through the SCN and causes the high $PeakO_1$ values observed in Figure 8.5.

The number of nodes and the divergence of the SCN are both significant and have a relative high impact on the BWE, but such impact is lower than that of the number of echelons, as it can be deducted from partial $R^2$ in Table 8.5. More specifically, the number of nodes is slightly more significant than the divergence of the SCN. SCNs with higher number of nodes show higher BWE, and SCNs with higher divergence show higher BWE, both factors following a linear trend.
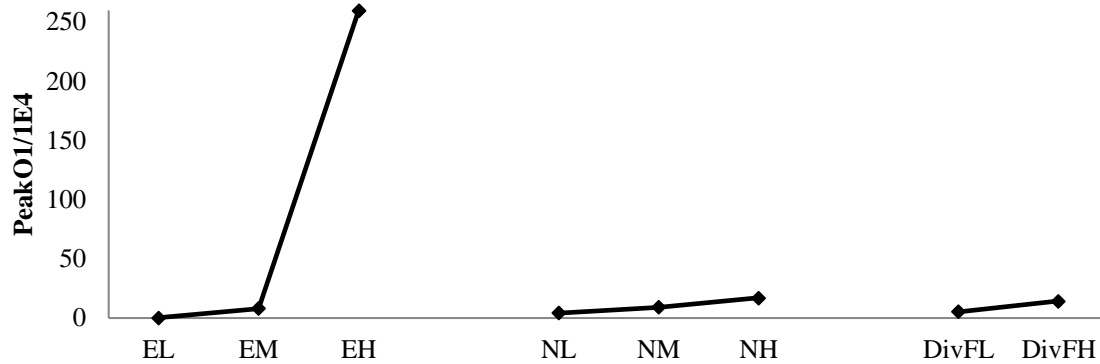
**Figure 8.5.** Main effects in Shock Lens scenario.

There are two significant interactions in this scenario. The most important is the number of echelons and the divergence of the SCN. As in the variance lens scenario, interaction plots as well as single-variable tests are used to determine the interaction between factors. Once again, the natural logarithm is used to transform the exponential interaction curves into linear curves in order to clarify its interpretation. In Figure 8.6 it can be seen that the linearized interaction curves are not parallel, which means that an interaction occurs between both factors. The *DivFH* curve shows a higher slope than the *DivFL* curve. Therefore BWE is more sensitive to the number of echelons in SCNs with high divergence than in SCNs with low divergence (see partial $R^2$ in Table 8.6). In addition, BWE is more sensitive to the divergence of SCNs with high number of echelons than SCNs with low number of echelons (see partial $R^2$ in Table 8.6). These results are confirmed by the single-variable test in Table 8.6, where all contrast were statistically significant ($p<0.001$).



**Figure 8.6.** Interaction between *E* and the *DivF* in Shock Lens scenario.

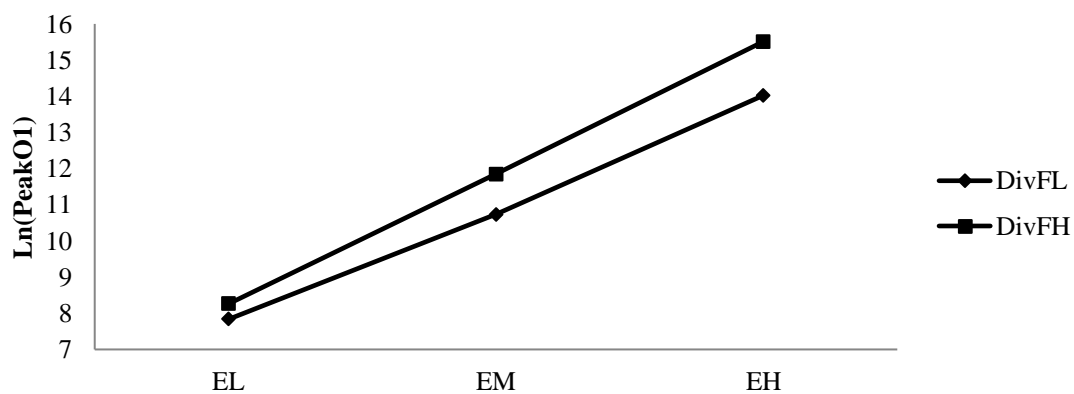**Table 8.6.** Single-variable test for the interaction between $E$ and $DivF$ in Shock Lens scenario.

| A contrast of the effect of $DivF$ for each level of $E$ | | | |
|---|---|---|---|
| **Echelons** | **$F$-ratio** | **$p$-value** | **$R^2$ (percent)** |
| Low | 41.010 | <0.001 | 1.5 |
| Medium | 282.493 | <0.001 | 9.5 |
| High | 501.283 | <0.001 | 15.7 |
| A contrast of the effect of $E$ for each level of $DivF$ | | | |
| **Divergence** | **$F$-ratio** | **$p$-value** | **$R^2$ (percent)** |
| Low | 4343.363 | <0.001 | 76.4 |
| High | 5954.338 | <0.001 | 81.6 |

The other significant interaction occurs between the number of nodes and the divergence of the SCN, but it has a lower $R^2$ than the previous interaction. BWE is more sensitive to the number of nodes in SCNs with a high divergence factor than in SCNs with a low divergence factor. Moreover, BWE is more sensitive to the divergence of SCNs with medium or high number of nodes than SCNs with low number of nodes. These results are supported by the single-variable test in Table 8.7, where all contrast were found to be significant ($p<0.001$).

**Table 8.7.** Single-variable test for the interaction between $N$ and $DivF$ in Shock Lens scenario.

| A contrast of the effect of $DivF$ for each level of $N$ | | | |
|---|---|---|---|
| **Nodes** | **$F$-ratio** | **$p$-value** | **$R^2$ (percent)** |
| Low | 142.922 | <0.001 | 5.1 |
| Medium | 286.426 | <0.001 | 9.6 |
| High | 279.612 | <0.001 | 9.4 |
| A contrast of the effect of $N$ for each level of $DivF$ | | | |
| **Divergence** | **$F$-ratio** | **$p$-value** | **$R^2$ (percent)** |
| Low | 171.984 | <0.001 | 11.4 |
| High | 275.228 | <0.001 | 17.0 |

### 8.4.3. A comparison between the variance lens scenario and the shock lens scenario

There are three important differences between the variance and the shock lens scenarios. First of all, the number of nodes and the divergence of the SCN have a higher impact on the BWE in the shock lens scenario than in the variance lens scenario (see $R^2$ in Tables 8.3 and 8.5). This fact is confirmed by comparing the main effects of the

number of nodes and the divergence of the SCN in both scenarios (see Figure 8.7), obtaining that $PeakO_1$ curves show higher slopes in the shock lens scenario than in the variance lens scenario and hence, BWE is more sensitive to these factors in the former scenario than in the latter. The higher number of nodes per echelon and/or the presence of critical echelons (SCNs with high divergence) make the SCN more vulnerable to an unexpected shock in demand and the consequent multi stock-out situation.
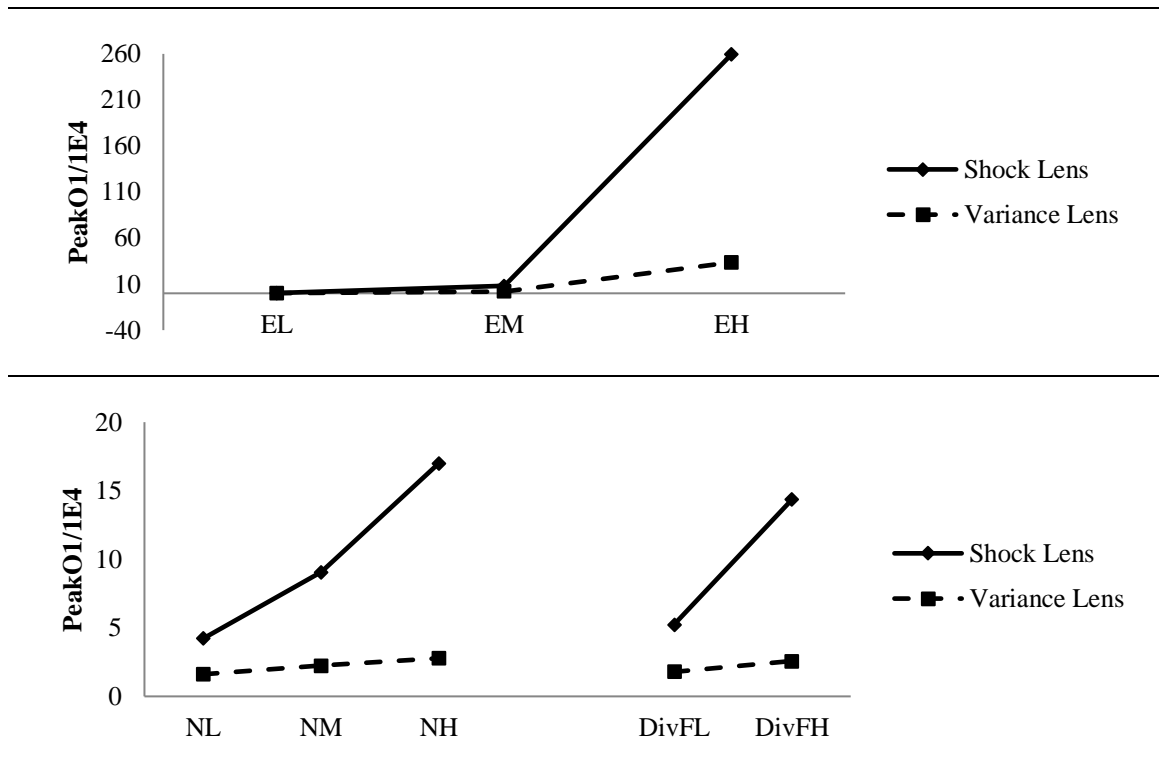


**Figure 8.7.** A comparison of the main effects of *E, N* and *DivF* between Variance Lens and Shock Lens scenarios.

A second important difference between both scenarios is that the BWE is higher in the shock lens scenario in all cases with a 95% confidence level (see Table 8.8 and Figure 8.7). Furthermore, since the shock lens scenario presents higher values of $PeakO_1$ and higher slopes than the variance lens scenario, the discrepancies in terms of BWE between both scenarios increase as the levels of the three structural factors become higher. In order to quantify these discrepancies a measure of the relative increment of the average BWE is employed in the shock lens scenario over the average BWE in the variance lens scenario (see equation 8.3).

$$\Delta = \frac{(PeakO_1^{shockLens} - PeakO_1^{varianceLens})}{PeakO_1^{varianceLens}} * 100 \qquad\qquad (8.3)$$

By plotting $\Delta$ for each level of the structural factors in Figure 8.8, in fact, it can be observed how the discrepancies between both scenarios show an increasing linear trend for each factor. Focusing on this figure, it can be noted that the curve for the number of echelons show the highest slope. Thereby, the number of echelons has the highest impact on $\Delta$. Meanwhile, the number of nodes and the divergence of the SCN have similar slopes (the slope of the former slightly higher than the slope of the latter), thus having similar impacts on $\Delta$.

**Table 8.8.** Average $PeakO_1$ and 95% confidence intervals from ANOVA.

| Factor | Level | Lens | Average $PeakO_1/1E4$ | 95% confidence Lower Bound | 95% confidence Upper Bound |
|---|---|---|---|---|---|
| Echelons | Low | Variance | 0.155 | 0.147 | 0.163 |
| | | Shock | 0.313 | 0.293 | 0.334 |
| | Medium | Variance | 1.929 | 1.833 | 2.030 |
| | | Shock | 8.009 | 7.504 | 8.548 |
| | High | Variance | 33.591 | 31.925 | 35.344 |
| | | Shock | 259.515 | 243.143 | 276.990 |
| Nodes | Low | Variance | 1.612 | 1.532 | 1.696 |
| | | Shock | 4.224 | 3.958 | 4.509 |
| | Medium | Variance | 2.237 | 2.126 | 2.353 |
| | | Shock | 9.058 | 8.487 | 9.668 |
| | High | Variance | 2.778 | 2.640 | 2.922 |
| | | Shock | 16.976 | 15.905 | 18.119 |
| Divergence Factor | Low | Variance | 1.804 | 1.730 | 1.880 |
| | | Shock | 5.226 | 4.955 | 5.511 |
| | High | Variance | 2.576 | 2.471 | 2.685 |
| | | Shock | 14.352 | 13.609 | 15.137 |

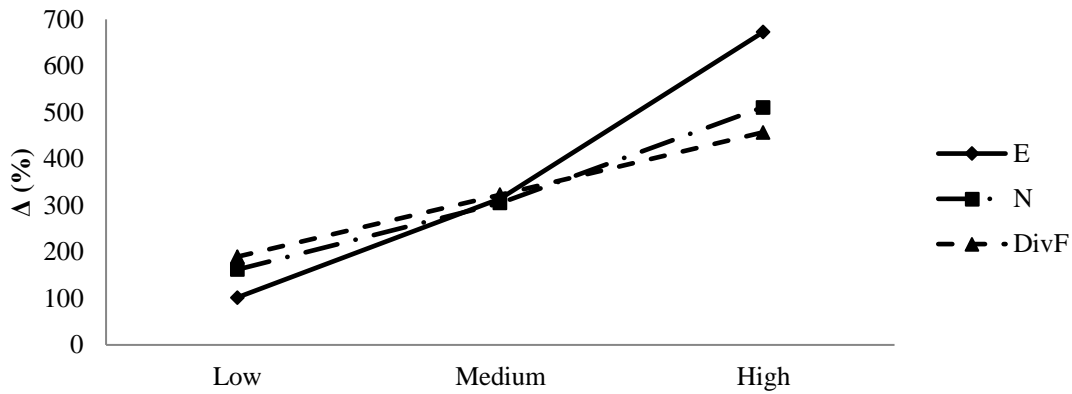**Figure 8.8.** BWE discrepancies between Variance Lens and Shock Lens scenarios.

Finally, the third important difference between both scenarios refers to the interactions between the structural factors: while there is a significant interaction between the number of echelons and the number of nodes in the variance lens scenario, in the shock lens scenario the significant interactions take place between the divergence with the number of nodes and the number of echelons. A summary of findings is shown in Table 8.9.

## 8.5. SUMMARY AND CONCLUSIONS

The structural design of the SCN, defined by the number of echelons, the number of nodes and the divergence of the SCN, has been analyzed in terms of BWE. A collection of divergent SCNs with random structures according to different levels of their structural factors have been modeled and simulated, and output data has been statistically analyzed. Two independent scenarios with different demand patterns have been considered: the former is characterized by a stationary and normally distributed demand input, while the latter is characterized by a normally distributed demand input which suffers, at a given time, a violent increment in mean. It has been shown that, in fact, the structural design of a SCN is statistically significant and influences the BWE in both scenarios: increasing the number of echelons, nodes, or the divergence of the SCN, will increase BWE. Furthermore, BWE is always higher in the case of an impulse in the end-customer demand. Additionally, BWE is more sensitive to the structural design of the SCN in this scenario than in the scenario with stationary demand. Hence, as SCNs size increases in terms of number of echelons or number of nodes, or increases its divergence, they also become more vulnerable to unexpected violent changes in demand

mean. In other words, as SCNs become more complex, they fall in a more vulnerable situation under uncertainties in market demand.

There are some managerial implications that can be derived from this work. The effect of the number of echelons (horizontal complexity) on the BWE has been widely analyzed in literature, mostly in serial SCNs. This study, through a statistical analysis of different structural designs, shows that the amplification of the variability of orders caused by the number of echelons persists in divergent SCNs. Hence, solutions proposed by other authors, like the elimination of channel intermediaries (Disney and Lambrecth, 2008), are also applicable.

Factor $N$ is related to the average number of nodes (or entities) within each echelon, also known as vertical complexity. Since the analysis focuses on divergent SCNs, the level of $N$ is directly related to the number of retailers (e.g. a high value of $N$ also means a high number of retailers). The present study shows that this factor has a direct impact on BWE. Therefore, managers and designers should pay special attention in optimizing the geographical distribution of entities in each echelon to avoid unnecessary stock points and retailers, thus limiting the factor $N$ and reducing the BWE.

The last structural factor analyzed, $DivF$, describes the distribution of nodes along the echelons of the SCN. The present study shows that this factor has a direct impact on BWE. Hence, managers and designers should try to smoothly increase the number of entities downstream to avoid the presence of critical echelons, in which a few entities have to deal with the supply of a high number of other entities in the subsequent echelon which, in fact, increases the BWE.

All the above implications are more critical for SCNs in a shock demand situation, i.e., SCNs facing unpredictable violent changes in demand mean. In this case, BWE is much more sensitive to the structure of the SCN than in the case of a stationary demand. Due to the important economic lost caused by the BWE, in this situation it is necessary to reorganize the structure of SCN. Other options are a good analysis of the market tendencies to anticipate these violent changes and the use of certain techniques to smooth the BWE, like information sharing or smoothing replenishment rules.

**Table 8.9.** A summary of findings.

| | Variance Lens | Shock Lens | Variance Lens Vs Shock Lens |
|---|---|---|---|
| **Factors** | All the studied factors impact on performance with different magnitude. In particular *E* reveals the highest impact. | All the studied factors impact on performance with different magnitude. In particular *E* reveals the highest impact. | In both scenarios all the factors are statistically significant. Even though, the impact of factors noticeable differs: *N* and *DivF* have a higher impact in the shock lens scenario. |
| | As the levels of the factors increase, the BWE always increase but with a different magnitude. More specifically, BWE exponentially increases as the structure shifts from an *EL* configuration to an *EH* one, and linearly increases as the structure shifts from a *NL* to *NH* and from *DivFL* to *DivFH*, respectively. | As the levels of the factors increase, the BWE always increase but with a different magnitude. More specifically, BWE exponentially increases as the structures shifts from an *EL* configuration to an *EH* one, and linearly increases as the structure shifts from a *NL* to *NH* and from *DivFL* to *DivFH*, respectively. | BWE is always higher in the shock lens scenario and main effect curves show higher slopes, thus showing a higher sensitivity of BWE to variations of the structural factors. |
| | | | As the levels of the factors increase, the discrepancies between both scenarios increase following a linear trend. These discrepancies are especially sensitive to *E*. |
| **Interactions** | Only the interaction *E*N* reveals a significant impact. | The interactions *E*DivF* and *N*DivF* are statistically significant. | Statistically significant interactions completely differs between both scenarios: |
| | As *E* increases, BWE is characterised by a lower sensitivity to *N*. Furthermore, as *N* increases, BWE is characterised by a lower sensitivity to *E*. | As *E* increases, BWE is characterised by a higher sensitivity to *DivF*. Furthermore, as *DivF* increases, BWE is characterised by a higher sensitivity to *E*. | Variance Lens: *E*N* |
| | | As *DivF* increases, BWE is characterised by a higher sensitivity to *N*. However, as *N* increases, BWE is characterised by an almost unaltered sensitivity to *DivF*. | Shock Lens: *E*DivF* and *N*DivF* |

# PART IV

## Conclusions and further research

# Chapter 9: Conclusions and further research

## 9.1. INTRODUCTION

BWE has been extensively investigated in the past years, and several root causes have been identified by researchers. However, most of these causes refer to operational or behavioral aspects of the SCN (i.e. lead time, risk pooling, forecasting, etc.), omitting how the companies are arranged or, in other words, the structure of the SCN. The only exception is the number of echelons, which has been identified as one of the main causes of the BWE. The reason is that, due to methodological problems and mathematical intractability of complex systems, one of the main common assumptions is that SCNs present a dyadic, a single-echelon or serially-linked configuration. These configurations are often limited to a few echelons, a few nodes and simple interrelations. However, modern SCNs, due to the outsourcing phenomenon rarely present these configurations, resulting in more complex structures like divergent, convergent or conjoined, with a high number of nodes and echelons, and several customers or provider. This increment in complexity requires SCNs to be analyzed on the network level, which adds more interrelations, dynamics, and complexity as compared to the more basic and linear chain level (Moser *et al*., 2011). Furthermore, SCM has focused on linear relationships of buyers and suppliers, useful for planning certain mechanical aspects of transactions between buyers and suppliers, but it fails to capture the complexity needed to understand a firm's strategy or behavior, as both depend on a larger supply network that the firm is embedded in (Kim *et al*., 2011).

In order to analyze the BWE phenomena in such SCNs, a modern methodology (MAS) has been employed to develop a SCN simulation platform (SCOPE) that is able to cope with the limitation of complex structures. A framework that exploits the reusability characteristic of the agents allows modeling a high number of companies and almost any kind of possible configuration by individually defining their interactions. Furthermore, its two-layer design allows modeling at two levels of details: intra-enterprise relations and inter-enterprise relation. Its modular design and its low level programming (Java) allow individually improving and customizing the desired agent,

easily introducing new policies and behaviors. After its validation, SCOPE has been used to break the limitations concerning to the structure of the SCN and explore the BWE in more complex SCN configurations. More specifically, the study has been focused on the divergent SCN by performing three different experiments. These experiments and their results are summarized in the next section.

## 9.2. MAIN CONCLUSIONS

The three experiments performed in this Thesis and their main results are:

i.  A comparison between a serial four-echelon SCN with a divergent four-echelons SCN under two different demand patterns (related to the variance lens and the shock lens, Towill *et al*., 2007). It has been found that:

   a. Variance lens, i.e. stationary demand signal. In this case the performance of both SCNs is very similar, being just a little worse for divergent SCNs.

   b. Shock lens, i.e. demand signal suffers an unexpected violent change. In this case the performance of the divergent SCN is much worse than that of the serial SCN, showing higher variance of orders and taking more time for recovery, incurring in higher costs and thus concluding than the divergent SCN is less robust than the serial SCN.

ii. A comparison of the performance of two BWE-avoidance strategies (information sharing and smoothing replenishment rule) between the serial SCN and the divergent SCN under the shock lens. It has been found that:

   a. Both strategies effectively reduce BWE in the divergent SCN. As in the serial SCN, information sharing performs better than the smoothing replenishment rule, and the combination of both techniques obtain the best results.

   b. The discrepancies between both SCN are reduced, thus increasing the robustness of the divergent SCN. However, these discrepancies still persist, not being completely removed.

iii.    Analysis of the impact of the SCN structure on the BWE through a full factorial design of experiments, in which the configuration of the SCN is systematically varied through its different structural factors. The BWE is analyzed under two different demand perspectives (the variance lens and the shock lens) by performing a statistical analysis (ANOVA). It has been found that:

a.  The structure of the SCN impacts the BWE, obtaining that all the structural factors are significant: (1) the BWE increases as the number of echelons (functional levels or channel intermediaries) increases, following an exponential trend; (2) the BWE increases as the average number of nodes (companies) within each echelon increases, following a linear trend; (3) the BWE increases as the divergence of the SCN (increment of nodes between consecutive echelons) increases, following a linear trend.

b.  The structure of the SCN shows a higher sensitivity to the BWE in the shock lens scenario.

## 9.3. RESEARCH PRODUCTION

This section summarizes the research production of the Thesis.

### 9.3.1. Journals

➢ Domínguez, R., Framinan, J.M., Cannella, S. Serial versus divergent supply chain networks: a comparative analysis of the bullwhip effect. *International Journal of Production Research* (2012 Impact Factor: 1.460). In press. Estimated publication day: 04/12/2013. DOI: 10.1080/00207543.2013.860495.

➢ Domínguez, R., Cannella, S., Framinan, J.M. On bullwhip-limiting strategies in divergent supply chain networks. *Computers and Industrial Engineering* (2012 Impact Factor: 1.516). Accepted. Estimated publication date: 2014.

➢ Domínguez, R., Framinan, J.M., Cannella, S. The impact of the supply chain structure on bullwhip effect. *European Journal of Operational Research* (2012 Impact Factor: 2.524). Under review.

➢ Domínguez, R., Framinan, J.M. 2013. A decision management tool: Modelling the order fulfilment process by multi-agent systems. *International Journal of Management and Decision Making*, 12 (3), 240-258. (in Scopus).

### 9.3.2. Conferences

➢ Domínguez R., Cannella S., Bruccoleri M., Framinan J.M. Arborescent Supply Chain Dynamics: the impact of OUT policies. *Proceedings of the 20th European Operations Management Association Conference*, Dublin, June 10-12, 2013.

➢ Domínguez R., Framinan, J.M., Cannella, S., Póvoa, A.P. Using multi-agent systems to explore information sharing in arborescent supply chain networks. *Proceedings of the 5th International Conference on Industrial Engineering and Systems Management,* Rabat, October 28-30, 2013.

➢ Cañizares, R.D., Framiñán, J.M. 2012. Development of a multi-agent platform for supply chain-wide order fulfillment. *Proceedings of the 4th International Conference on Agents and Artificial Intelligence*, 2, 203-208.

➢ Domínguez, R., Framinan, J.M., Dios, M.A., León, J.M. Revisión del estado del arte en modelado del *order fulfillment process* mediante sistemas multi-agente. *XIV Congreso de Ingeniería de Organización*, September 8-10, 2010.

### 9.4. FURTHER RESEARCH LINES

The limitations of the present work also represent opportunities for further research. First, in order to simplify the analysis, this work has been focused on divergent SCNs. Once the structure of the divergent SCN has been analyzed and its impact on the BWE has been determined, this study can be extended to other SCN configurations, like convergent or conjoined SCNs. Secondly, since the focus of the analysis was the structure of the SCN, other operational factors (forecast method, inventory policy, lead time, order batching, etc.) have been maintained fixed. Hence, a further research in which common operational factors are variables is needed in order to determine their relative importance in such SCNs as well as some possible interactions with their structural factors.

There is also some research implications derived from this work. As it was reported in Chapter 2, SCNs are complex systems and thus, the analysis performed on this field should turn on considering complex SCNs in further studies, in order to get closer to the dynamics of real SCNs. The present work is a step through modeling SCNs as complex systems. According to Reiß (1993), four dimensions of complexity exist:

1. Multiplicity, which leads to the variety of a system.

2. Variance, resulting in the heterogeneity of the system.

3. Changeability, determining the dynamic behavior of the system.

4. Ambiguity, leading to uncertainty.

In the current work, one of these drivers of complexity is addressed: the multiplicity. As compared with the traditional serial SCN, the divergent SCNs analyzed here have a higher number of elements and interdependence. In order to better understand complex SCNs, future research should consider exploring all the dimensions of complexity identified by Reiß (1993). In other words, future research should focus on modeling SCNs with high number of elements and interdependence (multiplicity), including diversity of elements, i.e., elements are different between them (variance, heterogeneity), and the ability of elements to change their status over time (changeability, chaos), as well as ambiguity and uncertainty.

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# Appendix A: Abbreviations

| | |
|---|---|
| ADE | Agent Development Environment |
| ANOVA | ANalysis Of Variance |
| APVIOBPCS | Automatic Pipeline Variable Inventory and Order Based Production Control System |
| ATP | Available To Promise |
| ATO | Assemble To Order |
| BWE | Bullwhip effect |
| BwSl | Bullwhip Slope |
| CAS | Complex Adaptive System |
| DOF | Degree Of Freedom |
| DSOPP | Distributed Simulation of Order Promising Protocols |
| FCFS | First Come First Served |
| GUI | Graphical User Interface |
| IDE | Integrated Development Environment |
| IOBPCS | Inventory and Order Based Production Control System |

| | |
|---|---|
| IQL | Information Quality Level |
| JADE | Java Agent Development framework |
| LPT | Longest Process Time |
| MAS | Multi-Agent System |
| MASCF | Multi-Agent Supply Chain Framework |
| MASON | Multi-Agent Simulator of Networks |
| MD | Make-Deliver |
| MRP | Material Resource Planning |
| MTO | Make To Order |
| MTS | Make To Stock |
| NPMA | N-Periods Moving Averages |
| NPMV | N-Periods Moving Variances |
| OFP | Order Fulfillment Process |
| ORVR | Order Rate Variance Ratio |
| OUT | Order Up To |
| RFQ | Request For Quotation |
| SCC | Supply Chain Council |

| | |
|---|---|
| SCM | Supply Chain Management |
| SCML | Supply Chain Modeling Language |
| SCN | Supply Chain Network |
| SCOPE | *Sistemas COoperativos para la Producción y Ejecución de Pedidos* |
| SCOR | Supply Chain Operations Reference |
| SD | Source-Deliver |
| SES | Simple exponential smoothing |
| SISCO | Simulator for Integrated Supply Chain Operations |
| SMA | Simple Moving Averages |
| SMD | Source-Make-Deliver |
| SPT | Shortest Process Time |
| Std Dev. | Standard Deviation |
| WMA | Weighted Moving Averages |
| XML | eXtensible Markup Language |