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A Reengineering Methodology for Supply Chain Networks Operating under Disruptions

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Abstract. Supply Chain Networks (SCN) are very complex organisational systems, and their reengineering gives rise to major projects which must be carefully planned and managed. These projects must follow a comprehensive analysis and design methodology taking into account all the problem facets, and they must be supported with appropriate computer-aided analysis and modeling tools. This paper proposes such a comprehensive SCN reengineering methodology for businesses operating in an uncertain environment. After discussing the problem, and the relevant literature, the activities of the methodology are presented and illustrated for a particular case: the location-transportation problem under uncertainty.

Keywords. Supply chain network design, uncertainty, robustness, resilience, network disruptions, multihazards.

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1. Introduction

Goods are procured, produced and distributed to customers using Supply Chain Networks (SCN) involving several facilities owned by a company, or a set of collaborating companies. These networks are engineered or reengineered through strategic decisions on the number, location, capacity and mission of their production-distribution facilities. Decisions on the selection of suppliers, subcontractors and 3PLs, and on the offers to make to product-markets, may also be involved. These strategic decisions shape the structure of the network but, once implemented, the SCN is used on a daily basis to respond to customers' demands, and possibly to unforeseen disruptions. Day-to-day procurement, production, warehousing, transportation and demand management decisions trigger product flows in the network, with associated costs, revenues and service levels. The adequate design of a SCN requires the anticipation of these future demands, flows, costs, revenues and service levels. An important issue is the performance measures used to evaluate the quality of the network designed. Return-on-investment measures, such as the *Economic Value Added* (EVA), are often used by strategic decision makers in this context, but the SCN design robustness is also an important dimension to consider.

A major preoccupation of contemporary businesses is the consideration of risk when designing SCNs. Since SCNs must be designed to last for several years, it is clear that they should be robust enough to cope with all the random environmental factors (supply, demand, prices, exchange rates…) affecting the normal operations of a company. In addition, SCNs should perform well under major disruptions. In view of recent events, such as the 9/11 terrorist attacks on WTC, hurricane Katrina, and the 2010 Haiti and Chile earthquakes, companies are aware that they should prepare for the next disaster, but in reality only a few do (Lee, 2004; Sheffi, 2005). At a point in time when management strives to make supply chains as lean as possible such disruptions may have serious impacts on company performances (Hendricks and Singhal, 2005). Rice and Caniato (2003) and Christopher and Peck (2004) investigate SCNs vulnerability to extreme unforeseen events such as natural disasters and strikes, and Sheffi (2005) examine the case of several companies who suffered from fires, earthquakes, floods, intentional attacks, etc. SCNs can be geographically dispersed across large regions which increase their exposure to extreme events and, in order to design robust networks, the impact of such plausible events must be considered. More specifically, SCNs should be designed to avoid risks as much as possible and to be resilient. Looking at the current SCN design literature from this point of view, Klibi *et al.* (2010) highlight its major drawbacks.

SCNs are very complex organisational systems, and their reengineering, in real life, gives rise to major projects which must be carefully planned and managed. These projects must follow a comprehensive analysis and design methodology taking into account all the problem facets

previously discussed, and they must be supported with appropriate computer-aided analysis and design tools. This text proposes such a comprehensive methodology, and it is organized as follows. Section 2 presents the key concepts needed to design SCNs under uncertainty. It also introduces a specific SCN design problem, known as the location-transportation problem, which is used to illustrate the methodology. Section 3 explains the steps of the SCN reengineering methodology proposed, and it illustrates them for the location-transportation problem. Finally, conclusions are drowned. Note that although much of the following discussion is cast in a business context, the reengineering process proposed applies as well to other situations.

2. Reengineering SCNs under Uncertainty

Designing value-creating SCNs

SCN design problems deal with strategic decisions such as facility location, technology selection and capacity acquisition that require large investments. These investments must be weighted against projected resulting improvements to the future value of the firm. SCN reengineering decisions impose resource availability and utilization constraints on the users of the network which, through their daily supply, production and distribution actions, in response to customer demands, determine the return that will be obtained from these investments. It can be argued that the paramount goal of a business should be the sustainable creation of shareholder value (Yucesan, 2007). This can be partially measured using static financial performance indicators such as the economic value added (EVA) or the return on capital employed (ROCE) but, under uncertainty, coherent risk measures must also be used to evaluate SCN robustness. All these facets of the problem are considered in the SCN reengineering methodology proposed by Klibi and Martel (2009). Their methodology involves the explicit modeling of design and user response decisions over a multi-period planning horizon, and it takes the temporal hierarchy between the decisions made at the design and user response levels into account. The reengineering approach presented in this text is based directly on this methodology.

Consider a planning horizon covering several *planning periods* (years, seasons…) $t \in T$, as illustrated in **Figure 1**. At the beginning of the planning horizon, SCN reengineering decisions are made and after an *implementation period* the network reengineered becomes available for use during a *usage period* which may last several years. At the user level, managers make daily or weekly supply, production, distribution and demand management decisions to serve customers, and they react to disruptions on an ongoing basis. In order to model user response decisions, time is usually divided into short *working period*s (days or weeks) $\tau \in T^u$. The concatenation of the implementation and usage periods following a reengineering decision defines a SCN *reengineering cycle*. Several such cycles unfold in time as SCN reengineering decisions are made. Reengineering decisions are usually made on a rolling horizon basis; that is the only decisions imple-

mented when the problem is solved at the beginning of the horizon are the first reengineering decisions. Subsequent design decisions are considered as future opportunities to adapt the network to its evolving environment. Also, it is important to understand that it is through the user's short term response decisions that revenues and expenditures are generated during the SCN usage period, and therefore that value is created. Unfortunately, at the beginning of the planning horizon, the future is not known. The best that can be done is to anticipate, with the information available, what the users and the designer would subsequently do to respond and adapt to plausible future business environments, and thus to model the SCN value creation process. The approach used to anticipate the value of future operational and reengineering decisions has a major impact on the quality of the SCN designed. Also, an adequate characterization of the future SCN environment is required to obtain good value anticipations.
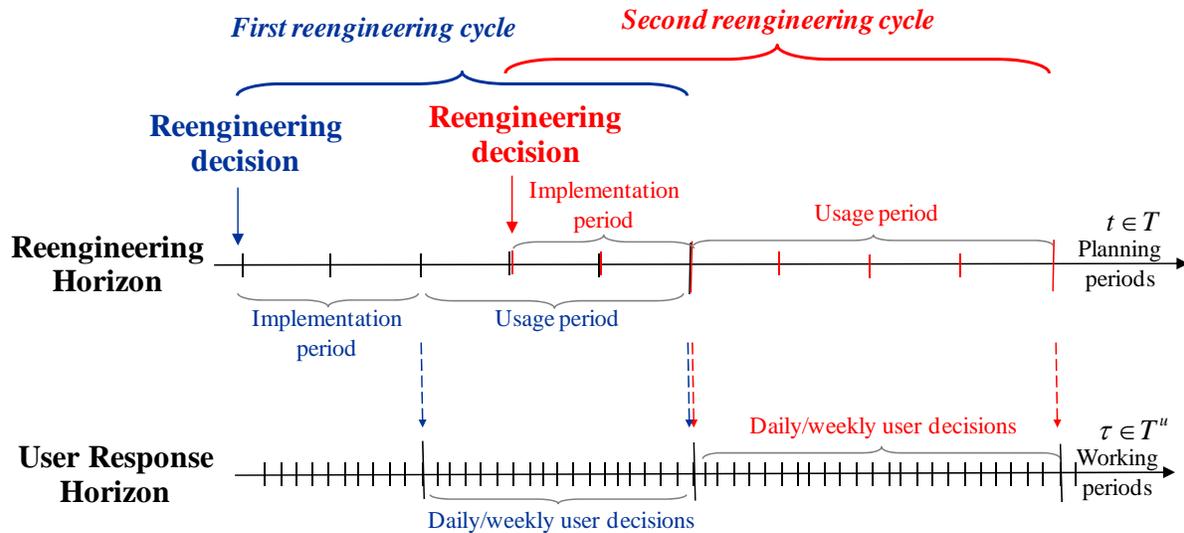
Figure 1. Decision Time Hierarchy for Two Reengineering Cycles

Taking uncertainty into account

Uncertainty is defined here as the inability to determine the true state of the future business environment which may be partially known or completely unknown. When some information is available, three types of uncertainties can be distinguished: randomness, hazard and deep uncertainty. Accordingly, three types of events should be considered to characterize SCN environments: random, hazardous and deeply uncertain events. The SCN reengineering methodology presented in this paper takes all these types of events into account and is based on recent work on catastrophe modeling (Grossi and Kunreuther, 2005), scenarios planning (Van der Heijden, 2005) and risk analysis (Haimes, 2004). It builds on the fact that the information available on the upcoming business environment can be presented in the form of a set of scenarios about how the future may unfold.

Random events describe factors with a probability of occurrence that can be estimated. Historic information on supply, demand, costs, lead times, exchange rates, etc., can be used to estimate the probability distribution of the random variables related to the business-as-usual operations of a SCN. These events include certain events, a particular case obtained when perfect information is available. *Hazardous events* describe factors or incidents affecting a number of adjacent working periods and leading to SCN disruptions. Hazards are rare but repetitive events which may be characterized by formal location, severity and occurrence processes. Hazardous events involve natural, accidental or wilful incidents affecting SCN resources. They include accidental disruptions in operations such as major equipment breakdowns, strikes and discontinuities in supply due to supplier bankruptcy, for example. They also include disruptions arising from natural disasters affecting a geographical region, such as earthquakes, floods, windstorms, volcanic eruptions, droughts, forest fires, heat waves, freezes and cold waves. In the recent past, events such as the Kobe earthquake, hurricane Katrina, Haiti and Chile earthquakes have provoked major disruptions to companies' SCNs and to countries critical infrastructures. For such events, catastrophe models have been used to provide likelihood of occurrence and/or likelihood of associated monetary losses, based on historical data and/or professional expert opinions (Grossi and Kunreuther, 2005). *Deeply uncertain events* are incidents affecting a number of adjacent working periods for which no directly relevant information exists. These events include isolated, non repetitive, extreme events for which a likelihood of occurrence cannot be evaluated (Banks, 2006). Events related to terrorism (sabotage, bombing…) and political instability (sudden currency devaluation, coup…), with unpredictable time of occurrence, severity and location, are usually considered as deeply uncertain. In the recent past, some of these disruptions such as the 9/11 WTC attack, the SARS epidemic and the US financial system crisis, have lead to major business failures. Lempert *et al.* (2006) suggest the elaboration of narrative scenarios for deep uncertainty situations, and show how to use these scenarios to enhance solution robustness.

Under randomness, some SCN variables (demands, prices, exchange rates…) are considered as random and their probability distributions can be estimated. The joint-events associated to the possible values of the random variables define a set of plausible future scenarios Ω^R, and a scenario $\omega \in \Omega^R$ has a probability of occurrence $p(\omega)$. High-impact hazardous events must also be taken into account but they cannot be treated the same way as low-impact business-as-usual events. Moreover, identifying potential threats and assessing their risk are very challenging undertakings. This is the domain of risk analysis which addresses three fundamental questions: 1) What can go wrong? 2) What is the likelihood of that happening? 3) What are the consequences? These questions are implicitly embedded in the SCN reengineering methodology proposed in the next section.

The first question leads to the identification of a set S of SCN *vulnerability sources*. These vulnerability sources are used to partition the set L of SCN locations into location subsets $L_s \subset L$, $s \in S$, affected in the same way by extreme events. For example, locations could thus be partitioned into supply sources, production-distribution sites and demand zones. This question also leads to the identification of the type of hazards threatening the SCN. Considering every possible type of hazard separately is too cumbersome, however, which brings forth the definition of a set H of *multihazards*, i.e. aggregate extreme events incorporating classes of relevant hazards (Gogu *et al*. 2005; Scawthorn *et al.*, 2006). Typical multihazards would be: natural disasters, geopolitical failures, market failures and industrial accidents. In order to answer the second question, the geographical territory in which the SCN performs must be partitioned into a set of *hazard zones Z*. Using geographical coordinates, the hazard zone $z(l) \in Z$ of a location $l \in L$ can be identified. Hazard zones delineate areas with similar geological, meteorological, political, economical and critical infrastructure characteristics. For each multihazard $h \in H$, a set G_h of zone aggregates called *exposure level* are then introduced. Exposure levels can be defined top-down but they are usually constructed by evaluating an *exposure index* for each zone, and associating levels to adjacent index value intervals. Each zone $z \in Z$ is then assigned to a level $g \in G_h$ based on its index value, thus defining a membership relationship $g_h(z)$ between zones and exposure levels. As illustrated in **Figure 2**, at this point, each SCN location $l \in L$ is associated to a vulnerability source $s(l) \in S$, a hazard zone $z(l) \in Z$, and exposure levels $g_h(z(l)) \in G_h, h \in H$. A compound stochastic process then needs to be defined for each exposure level to describe how multihazards occur in space and in time, and to specify incident's intensity and duration. The third question arises when the SCN is hit. The occurrence of an incident in a hazard zone does not necessarily result in a hit of all the SCN locations in that zone. Attenuation probabilities need to be defined to reflect hits likelihood. When a location is hit, the impact on the network resources and demand can be modelled using recovery functions based on intensity and time to recovery variables. The application of these concepts to the modeling of Canadian Forces humanitarian, peace keeping and peace enforcement missions, in response to natural catastrophes and armed conflicts, is found in Martel *et al*. (2010).

Defining plausible futures

The superposition, during the planning horizon, of a specific instance of such an hazard process, over specific instances of the business-as-usual random variables described previously, yield a probabilistic scenario $\omega \in \Omega^P$ with probability $p(\omega)$. Some of these plausible future scenarios may involve only a few multihazard over the planning horizon but others may be much more chaotic. An intuitive measure to assess the risk associated to a scenario $\omega \in \Omega^P$ is the number of hits it undergoes during the planning horizon. An alternative measure would be the cumulative damage level during the planning horizon. **Figure 3** illustrates the distribution of the

number of hits for a large sample of scenarios with exponential multihazard inter-arrival times. In order to distinguish between the scenarios a decision maker would consider as acceptable, in term of the risks involved, and those that would raise a serious concern, we define a hazard tolerance level κ. This level is the maximum number of hits (or the maximum cumulative damage level) the decision-maker can tolerate without serious concern. This tolerance level is used to partition the set of probabilistic scenarios Ω^P in two subsets: Ω^A a set of acceptable-risk scenarios, with associated acceptable-risk probability $\pi^A = \Sigma_{\omega \in \Omega^A} p(\omega)$ and conditional scenario probabilities $\pi^A(\omega), \omega \in \Omega^A$, and Ω^S a set of serious-risk scenarios, with associated serious-risk probability $\pi^S = \Sigma_{\omega \in \Omega^S} p(\omega)$ and conditional scenario probabilities $\pi^S(\omega), \omega \in \Omega^S$. This distinction is required to take into account the decision-maker attitude to risk when formulating a design model.
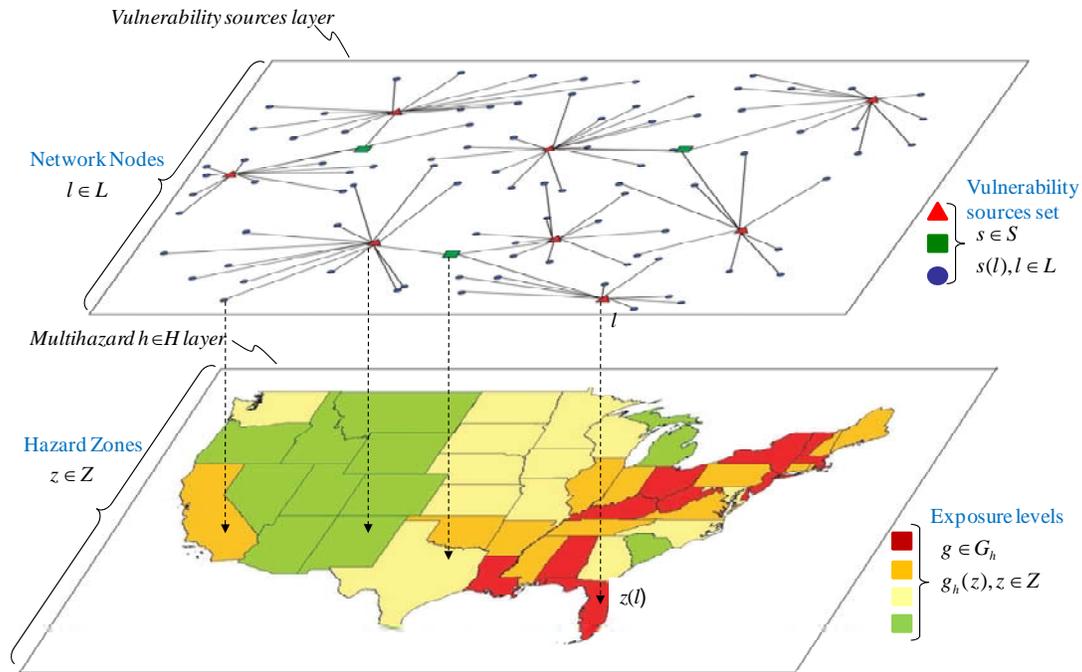
Figure 2. SCN Exposure Modeling

As indicated previously, probabilistic scenarios may completely overlook some potential extreme events for which no information and experience exist. It is to cope with these potential threats that imaginative deeply uncertain scenarios can be considered. However, for our purposes, these scenarios must be expressed quantitatively in terms of parameters which can be incorporated in a SCN design model. Moreover, these scenarios necessarily include random events and they may also include hazards so they are most easily elaborated by perturbating probabilistic scenarios. In what follows, our interest in the set Ω^U of deep uncertainty scenarios will be mainly related to our need to consider worst case scenarios. These would typically be probabilis-

tic scenarios in the tail of the distribution of the number of hits (see **Figure 3**) perturbed by deep-uncertainty events imagined by experts.
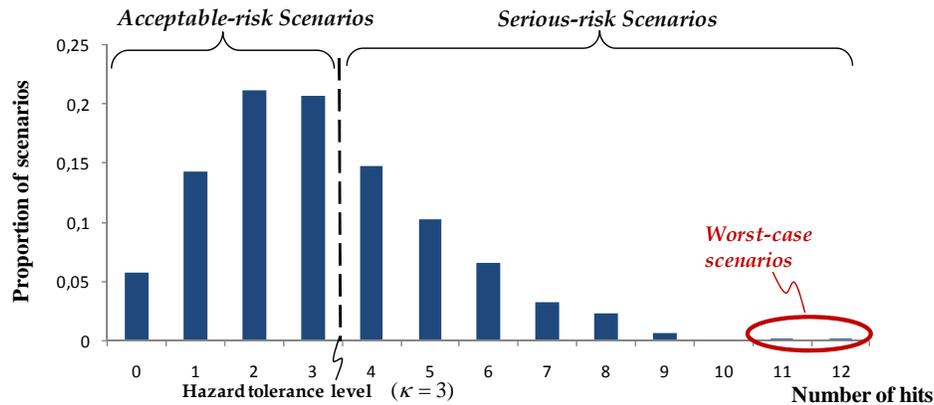
Figure 3. Distribution of the Number of Hits for a Large Scenario Sample

Businesses and organizations operate in a complex world and, when considering a long planning horizon, it cannot be assumed that the future will unfold in the tracks of the past. When developing plausible scenarios, companies like Shell study significant events, they analyse political, social and economic actors and their motivations, they explore what the world might look like over the next twenty years, and the impact of alternative views of the future on their business environment (*Shell Global Scenarios to 2025*, 2005). In other words, they define possible *evolutionary paths*. The scenarios in $\Omega = \Omega^P \cup \Omega^U$ are possible realizations of a set of underlying stochastic processes with known (for Ω^P) or unknown (for Ω^U) parameters. In what follows, it is assumed that a set K of evolutionary paths with probability $p_k, k \in K$, can be defined and that the parameters of the scenario generating stochastic processes depend on evolutionary paths. It is thus seen that the set of scenarios Ω is the union of the scenario sets Ω^{Pk}, Ω^{Uk} associated to the evolutionary paths $k \in K$, and that the probabilistic scenario probabilities $p_k(\omega)$ also depend on k. Our challenge now is to take all this into account in our SCN reengineering methodology.

Fostering SCN robustness under disruptions

Given the uncertainties discussed previously, it is clear that maximizing expected value is not sufficient. To achieve sustainable value creation, the SCN designed must also be robust. Several authors have discussed robustness in a SC context (Rosenblatt and Lee, 1987; Gutierrez *et al*., 1995; Mo and Harrison, 2005; Sheffi, 2005; Dong, 2006; Snyder and Daskin, 2006). They characterize robustness as the extent to which the SCN is able to carry its functions for a variety of plausible future scenarios. Linking this to the evaluation of SCN performance, it can be stated that a SCN design is robust, for the planning horizon considered, if it is capable of providing sustainable value creation under normal business conditions as well as major disruptions.

This definition provides means to evaluate the robustness of a SCN design. But, what kind of SCN structure is likely to be robust? More specifically, what kind of risk mitigation constructs should be incorporated in our reengineering models to obtain robust SCN designs? To answer these questions we need to look more closely at the notions of SCN *responsiveness* and *resilience*. At the operational level, short-term mitigation actions are required to deal with the variability of low-impact as well as high-impact business events: these are the domain of responsiveness policies. However, to deal with network threat situations, mitigation postures related to the SCN structure, but going beyond the standard reengineering decisions discussed previously, are required: these are the domain of resilience strategies. General discussions of enterprise resilience are found in Van Opstal (2007) and on the Web site of the Center for Resilience (www.resilience.osu.edu) who defines resilience as "the capacity of a system to survive, adapt, and grow in the face of unforeseen changes, even catastrophic incidents". Rice and Caniato (2003), Christopher and Peck (2004) and Sheffi (2005) conclude from empirical studies that business is in need of resilience strategies to deal effectively with unexpected disruptions. Several definitions of resilience and its relation with supply chain capabilities are reported in Pettit *et al.* (2010).

The aim of responsiveness policies is to provide an adequate response to short-term variations in supply, capacity and demand. They provide a hedge against randomness and hazards to increase the SCN expected value. For a given network structure, they shape the means that can be used to satisfy demands with available internal resources and with preselected external resource providers. Responsiveness policies are typically associated to resource flexibility mechanism, such as capacity buffers (Sabri and Beamon, 2000 and Chopra and Sodhi, 2004), production shifting (Graves and Tomlin, 2003), overtime and subcontracting (Bertrand, 2003); safety stock pooling and placement strategies (Graves and Willems, 2003); flexible sourcing contracts (Kouvelis, 1998; Semchi-Levi *et al.*, 2002; Lee, 2004; Sheffi, 2005; Tomlin, 2006); and shortage response actions, such as product substitution, lateral transfers, drawing products from insurance inventories, buying products from competitors, rerouting shipments or delaying shipments (Shen *et al.*, 2003; Gunasekaran *et al.*, 2004; Tomlin, 2006).

The aim of resilience strategies is to obtain a SCN structure reducing risks and providing capabilities for the efficient implementation of the responsiveness policies previously discussed. This can be done by avoiding or transferring risks (Manuj and Mentzer, 2008), and/or by investing in flexible and redundant network structures (Rice and Caniato, 2003; Sheffi, 2007). Avoidance strategies are used when the risk associated to potential product-markets, suppliers or facility locations is considered unacceptable, due for example to the instability of the associated geographical area. This may involve closing some network facilities, delaying an implementation, or simply not selecting an opportunity. Another way to avoid risks may be through vertical integra-

tion, i.e. the internalisation of activities. This may reduce risk through an improved control, but it converts variable costs into fixed costs. This is an incitation to produce internally for low risk product-markets and to outsource production for higher risk product-markets, thus transferring risks to suppliers. These are important tradeoffs that must be captured in SCN design models.

Responsiveness capabilities development may be flexibility or redundancy based. Flexibility based capabilities are developed by investing in SCN structures and resources before they are needed. Examples of reengineering decisions providing such capabilities include selecting production/warehousing systems that can support several product types and real-time changes, choosing suppliers that are partially interchangeable, and locating distribution centers to ensure that all customers can be supplied by a back-up center with a reasonable service level if their primary supplier fails. Redundancy based capabilities involve a duplication of network resources in order to continue serving customers while rebuilding after a disruption. An important distinction between flexibility and redundancy based capabilities is that the latter may not be used (Rice and Caniato, 2003). Examples of redundancy based capabilities include insurance capacity, that is maintaining production systems in excess of business-as-usual requirements, and insurance inventory dedicated to serve as buffers in critical situations (Sheffi, 2005). The consideration of such responsiveness capabilities complicates SCN design models considerably. The main challenge is to elaborate resilience strategies providing an adequate protection from disruptions without reducing the SCN effectiveness in business-as-usual situations.

In summary, to achieve sustainable value creation in a disrupted world, one must formulate models seeking to maximize the discounted sum of the residual cash flows generated over a multi-period planning horizon, considering the revenues and costs of the operational and contingency actions required to satisfy customers demands, and taking the three types of uncertainties identified into account through a set of plausible future scenarios. The reengineering methodology presented in the next section is based on such models.

The Location-Transportation Problem

In order to illustrate some aspects of the reengineering methodology proposed, in what follows, we use a simple but common SCN design problem: the location-transportation problem (LTP) under uncertainty. The LTP is a hierarchical decision problem due to the temporal hierarchy between the location decisions and the transportation decisions, and it is described in detail in Klibi *et al.* (2010). Briefly, the company considered purchases a family of similar products from a number of supply sources. This product is sold to customers located in a large geographical area and hence it must be shipped to a large number of ship-to-points. In order to serve its customers, the company must implement a number of capacitated depots with similar processes and technology. For a given day, the capacity of a depot reflects its maximum throughput in

terms of a standard shipping unit (ex: pallets). In addition to its regular capacity level, we assume that under normal business conditions, the depot can provide supplementary daily capacity using overtime. Customer orders follow a stationary stochastic process, and the company wants to provide next day delivery from a single source using common or contract carriers. To this end, several transportation options are available, namely: single customer full truckloads (FTL), single customer partial truckloads (STL), multi-drop truckloads (MTL) or less than truckload (LTL) transportation. For a given day, when all the orders are in, the company plans its transportation for the next day and it requests from its carriers the trucks required to deliver products to ship-to-points. However, the network's depots are under the threat of disruptions and, consequently, their capacity to respond adequately to ship-to-point's orders can be perturbed. Therefore, in order to complete the orders received for a given day, the company relies first on the regular capacity of the depot assigned to customers, second on overtime, and third on order transfers between depots. If this is not sufficient, external resources can be used to satisfy all orders. **Figure 4** illustrates the structure of the LTP under uncertainty. This problem is studied in depth by Klibi and Martel (2010a).
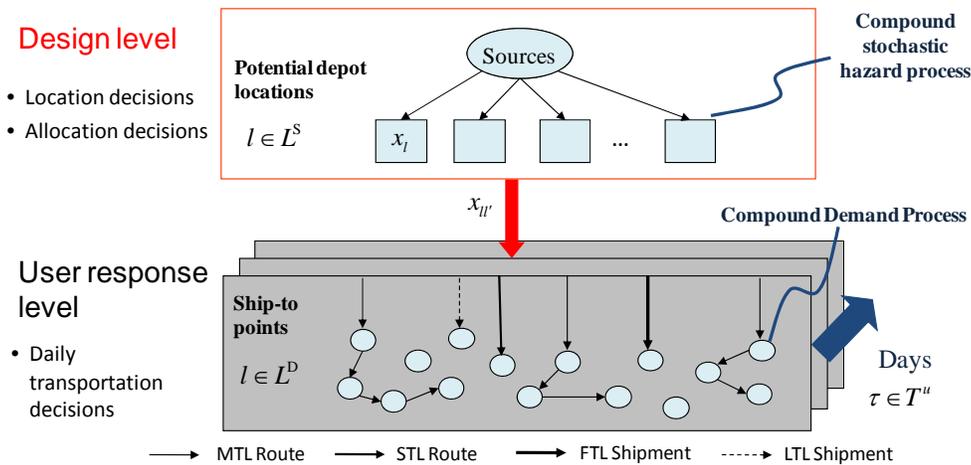
Figure 4. The LTP Structure under Uncertainty

3. SCN Reengineering Methodology

Supply chain networks are very complex systems and they are rarely engineered on a green field basis. In most practical cases, when a SCN design project is initiated, the objective is rather to improve a portion of an existing supply chain. In fact, SCN reengineering can be seen as a cyclical improvement process where parts of the network are periodically restructured. The SCN reengineering methodology proposed in this section is illustrated in **Figure 5**. The figure presents the main activities to be performed during a cycle and their respective deliverables (on the arcs). A reengineering cycle starts with a detailed study of the current SCN and of its business environment. This activity involves the collection and analysis of a lot of historical data, the prospec-

tive evaluation of evolutionary trends to identify future opportunities and threats, and strategic decisions on how the company would like to position its supply chain in the future. Based on these analyses, a SCN modeling activity is then undertaken. This involves mainly the elaboration of descriptive hazard models, and the formulation of normative design and user response models. The next activity involves the generation of plausible futures. These are mostly obtained using Monte-Carlo methods based on the hazard models and stochastic processes previously defined. Imaginative worst case scenarios can also be specified. Samples of scenario are then used to generate instances of the normative design model previously formulated. When these models are solved, a set of candidate designs is obtained. In the following activity, candidate designs (including the status quo) are evaluated, using adequate performance measures with a large set of plausible scenarios, and the best SCN structure is selected. Finally, the optimal design is implemented and eventually a new reengineering cycle will be initiated. The following sections explain each one of these reengineering activities in detail.
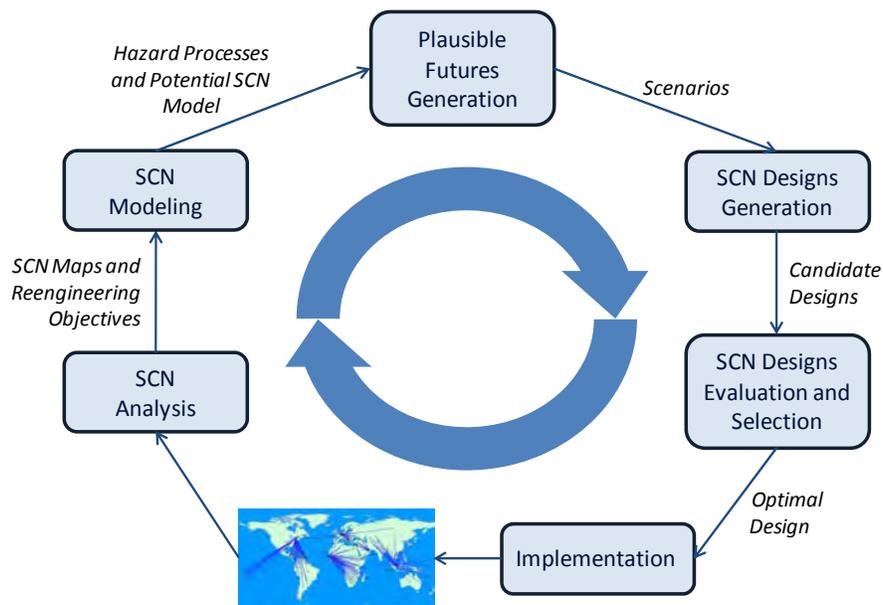
Figure 5. SCN Reengineering Cycle

SCN Analysis

The aim of this first activity is to understand the SCN and the business environment in which it is evolving, and to specify the reengineering cycle objectives and scope. The analysis must be done from three points of view: 1) the business is considered as an actor performing on the industrial scene, which leads to the analysis of markets, competitors and industry structures; 2) the SCN is viewed as a complex socio-technical system to understand, which requires structural, functional and performance analyses; and 3) the SCN is considered as a vulnerable system under threats, which gives rise to some risk analyses. These analyses provide the information required to perform a SCN diagnosis, thus identifying strengths, weaknesses, opportunities and

threats. Strategic supply chain development directions can then be elaborated to improve the competitive position of the company, and a specific reengineering project mandate can be specified.

Business Environment Analysis

Thorough business environment analyses are usually performed when a company prepares its strategic plans (Porter, 1980; D'Amboise *et al.*, 1995, Thompson and Strickland, 1999) and, in the context of a SCN reengineering project, available studies may provide most of the information required on markets, competitors and the industry. If the information is not readily available, however, one must at least make enquiries to identify emerging technologies (production, storage, transportation...), potential partners (suppliers, subcontractors, public warehouses, carriers, 3PLs...) and competitors (potential acquisitions, market shares...) that may contribute in improving the actual SCN. The nature of contracts with partners, capital and labour markets constraints, and environmental regulations must also be understood. The industry market structure and market development opportunities are particularly important inputs. The relationships between demand and value drivers such as product prices, response times and quality must be characterized, as well as long-term product-market expansion opportunities. Global economic trends and their impact on the company must also be examined. This leads to the elaboration of the set K of evolutionary paths to consider in the study.

SCN Processes, Structure and Performance Analysis

The structure and behaviour of the SCN is usually studied using data extraction and exploration tools, geographical information systems (GIS), mapping formalisms and statistical inference methods. These analyses require large amounts of historical data on products, customers, facilities, suppliers, subcontractors, carriers, sales, shipments, inventories, production quantities, etc., obtained mainly from the company databases and stored in a reengineering project database. At the structural level, the analyses performed provide a classification of products into product families, of ship-to-points into demand zones and product-markets, and of suppliers into supply zones. These classifications are often based on Pareto analysis, geospatial analysis and cluster analysis methods. Snapshots of the resources associated to current facilities and current partners are also elaborated. Finally, maps of the current SCN flow patterns between supply zones, facilities, and demand zones are also produced. Such a map, created for a Pulp and Paper company using a GIS, is illustrated in **Figure 6**.
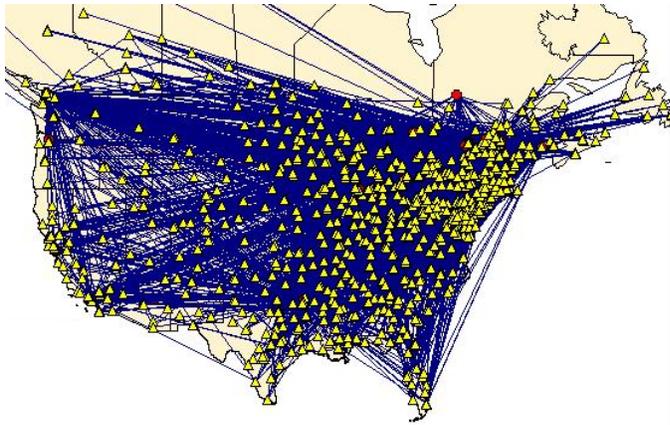
Figure 6. Current SCN Flow Map
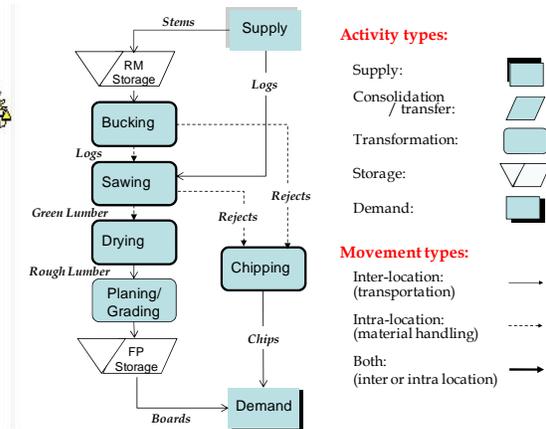
Figure 7. Activity Graph for a Sawmill
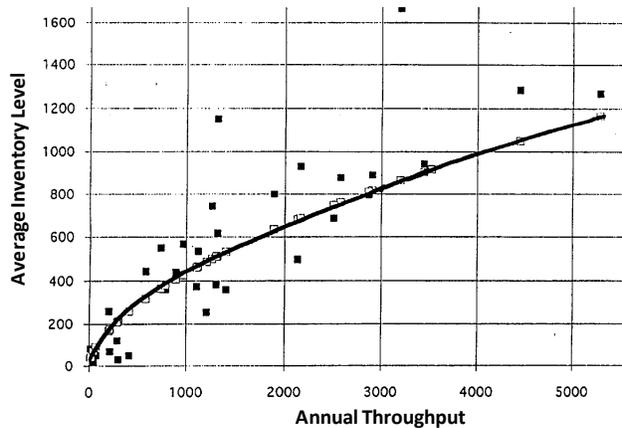
Figure 8. Inventory-Throughput Function
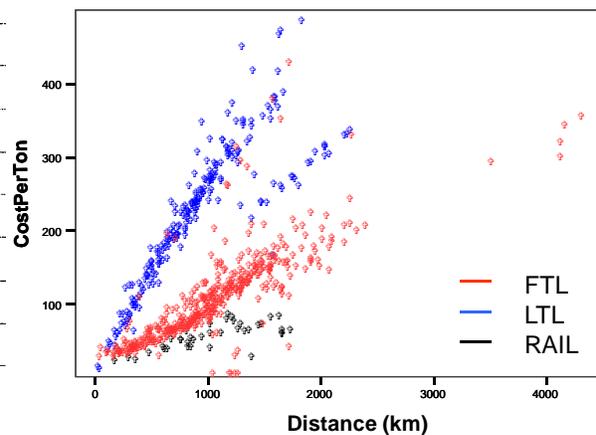
Figure 9. Shipments Cost-Distance Plot

At the functional level, the analyses made yield process diagrams describing the logic of the company production-distribution activities and of its planning and control methods. Activity graphs, such as the one showed in **Figure 7** for a typical sawing company, are used to describe physical processes. SCN response policies and method, related for example to the assignment of orders to depots and to the elaboration of shipping routes, can be described using data flow diagrams, flow charts or pseudo code. These, as we shall see, are required to formulate adequate design models and to evaluate alternative SCN designs. At this level, the supply, demand and resource consumption behaviours resulting from these processes, and the associated costs and revenues drivers, are also examined. This is done using data visualization methods such as histograms and resource usage profiles, as well as statistical methods such as time series analysis and regression analysis. Critical system parameters, probability distributions and relationship functions are thus estimated. For example, **Figure 8** shows an inventory-throughput function obtained for the storage of utility poles in an electricity company, and **Figure 9** shows a plot of (cost/ton, distance) points for all the shipments made from a pulp and paper mill during a year for three modes of transportation (used to estimate transportation cost functions). It is at this

resource consumption behaviours resulting from these processes, and the associated costs and revenues drivers, are also examined. This is done using data visualization methods such as histograms and resource usage profiles, as well as statistical methods such as time series analysis and regression analysis. Critical system parameters, probability distributions and relationship functions are thus estimated. For example, **Figure 8** shows an inventory-throughput function obtained for the storage of utility poles in an electricity company, and **Figure 9** shows a plot of (cost/ton, distance) points for all the shipments made from a pulp and paper mill during a year for three modes of transportation (used to estimate transportation cost functions). It is at this stage that the business-as-usual random variables to consider in the study are identified and characterized.

Another important dimension is the evaluation of SCN performances. Most companies follow their financial performances closely but they do not necessarily have a framework which directly relates supply chain activities to value creation. Also, in order to obtain sustainable value creation, one must not monitor performances only in term of expected value, but robustness measures and aversion to risk must be taken into account. The issue here is not as much to complete a thorough evaluation of the current SCN, but rather to elaborate a performance evaluation framework that will enable the company to formulate adequate SCN design models, and subsequently to evaluate candidate designs in order to identify the best one.

SCN Risk Analysis

At this point in the project, risk analysis involves mainly the identification and classification of the SCN threats arising from hazardous and deeply uncertain events. More specifically, it involves the classification of SCN locations L into vulnerability sources L_s, $s \in S$, and of hazards into multihazards H, as well as the zonation of the territory into hazard zones Z and the classification of these zones into exposure levels G_h, $h \in H$. As illustrated in **Figure 10**, when considering potential risks arising from natural, accidental and wilful hazards, a large set of vulnerability sources can be identified. However, the impact of hazards on these vulnerability sources can vary from catastrophic to low. At the strategic decision-making level, the number of vulnerability sources considered should be reduced to a manageable level. A filtering process based on a subjective evaluation of the vulnerability identified leads to the selection of the sources with potential strategic consequences to be considered in the reengineering project. The vulnerability sources S retained usually include the main internal production, distribution and service resources influencing capacity (plants, warehouses, stores…), the main product-markets or service-offers influencing demand, and the main vendors influencing supply (raw-material suppliers, energy suppliers…). It is assumed here that all strategic vulnerabilities are related to SCN locations $l \in L$ and not to its arcs. The overriding criterion for the definition of a vulnerability source $s \in S$ is that all the locations $l \in L_s$ it covers must have a similar behaviour in terms of impact

intensity, time to recovery and recovery pattern when hit by a multihazard, so that they can all be described in terms of the same metrics. They must also be defined so that the sets $L_s \subset L$, $s \in S$, are mutually exclusive and collectively exhaustive.
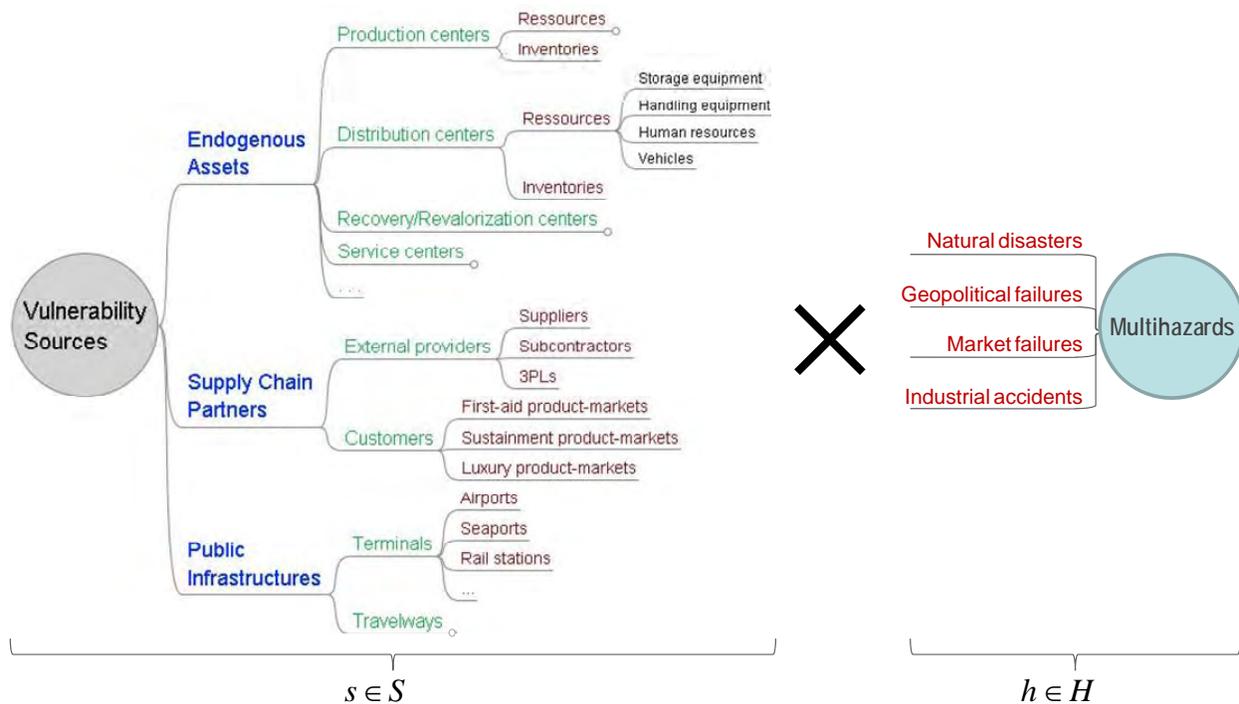
Figure 10. Examples of Vulnerability Sources and Multihazards

The specification of the multihazards set H to consider is also an important issue. Depending on the context of the study, some hazard types may not be relevant, and some vulnerability sources may be affected more by some hazards than by others. Also, the data related to some relevant hazards may not be available. The number of multihazards considered should be kept to a minimum while making sure that major (vulnerability source, multihazard) relationships are captured. This leads to the specification of vulnerability source threat domains, that is of subsets $H_s \subseteq H$ of multihazards which have an impact on a vulnerability source $s \in S$. Multihazards can be elaborated from the data provided by several public sources such as the Centre for Research on the Epidemiology of Disasters (www.cred.be), the Heidelberg Institute for International Conflict (www.hiik.de), the Federal Emergency Management Agency (www.fema.gov) and the U.S. Geological Survey (www.usgs.gov), and private sources such as Swiss Re (www.swissre.com) and Munich Re Group (www.munichre.com).

Zones Z delineating geographical areas with similar hazard characteristics must also be defined. These zones may correspond to 3-digit zip-codes, to counties, to states/provinces, to countries, or to a combination of those, depending on the level of precision desired and the data available. They must be constructed, however, to make sure that the SCN location aggregates defined (such as demand zones) fit uniquely in a hazard zone, and they must be large enough to consider

the occurrence of extreme events in different zones as independent. They must also be defined so that the sets $L_z \subset L$ of locations in the zones $z \in Z$ are mutually exclusive and collectively exhaustive. Finally, exposure levels can be defined top-down or buttom-up, depending on the context. Exposure levels are sometimes associated to geographical regions, such as continents. The states in the continent then provide a relationship $g_h(z)$ between zones and levels. Alternatively, levels can be constructed by evaluating an exposure index for each zone, and then associating levels to adjacent index value intervals. Zones are then assigned to levels based on their index value. The exposure index used to do this can be based on failed state (www.foreignpolicy.com) and/or opacity (www.opacityindex.com) indexes designed to reflect the political stability of a region, natural catastrophes exposure indexes calculated from the data provided by CRED, FEMA or USGS, economic performance indexes such as the World Competitiveness Scores of IMD (www.imd.ch) or the Global Competitiveness Index of WEF (www.weforum.org), industrial accident indexes related to the claims made to insurance companies, public infrastructure quality indexes calculated from databases such as the CIA World Factbook (www.cia.gov/cia/publications/factbook), or on a combination of those.

Diagnosis, Strategic Directions and Reengineering Mandate

The environmental, structural, functional, performance and risk analyses discussed previously provide the information required to perform a SCN diagnosis. This is often done by identifying strengths, weaknesses, opportunities and threats, and then by delineating critical success factors. Strategic supply chain development directions can then be elaborated to improve the competitive position of the company, and a specific reengineering project mandate can be specified. The former relates to product-market penetration targets, the specification of manufacturing stages and distribution echelons (by reengineering the activity graph), the identification of potential facility sites, suppliers, subcontractors and 3PLs, as well as of potential manufacturing, distribution and transportation capacity options. The later delimits the SCN boundaries for the reengineering project, and it specifies the planning horizon to cover, the random variables, vulnerabilities, multihazards and evolutionary trends to consider, the aggregation levels to use, the cost and inventory-throughput functions to apply, as well as the performance measures to utilize to evaluate alternative SCN designs.

To illustrate, for the location-transportation example introduced previously, the results of the analysis yields the following problem specifications. Since we are dealing with similar products having similar market and risk profiles, all products are aggregated in a single product family and aggregate demand quantities are measured in pallets. The company is considering a set L^S of sites where depots could be located, and it wants to provide next-day delivery to all the ship-to-points L^D of its United-States customers. For this reason, a depot $l \in L^S$ can supply only the ship-to-points $L_l^D \subseteq L^D$ which are close enough to be reached in one day. Aggregate day-to-day

demands from ship-to-points $l \in L^D$ are variable, and they follow a compound process with Exponential order inter-arrival times q_l and Log-Normal order size o_l. The cumulative distribution functions of inter-arrival times and order sizes are denoted respectively by $Exp_l(.)$ and $LN_l(.)$, $l \in L^D$. Also, to provide a better service, the company does not want to split customer orders. The fixed annual operating cost A_l incurred when a depot $l \in L^S$ is used was estimated, taking all relevant financial charges into account. The TL and LTL transportation means exploited by the company are classified into FTL, STL, MTL and LTL transportation options, and cost formulas based on distance and load are derived for each option. Product sales prices u_l for ship-to-points $l \in L^D$ and purchase prices v_l for depots $l \in L^S$ were calculated using weighted averages. Vehicles capacity b^F in pallets/load and daily depots capacity $a_l, l \in L^S$, in pallets/day, were also calculated, as well as overtime/regular-time capacity proportions φ_l and overtime costs v_l^z. The response policy of the company is applied using specific procedures for order assignment, transportation option selection and vehicle routing. Finally, when an order cannot be supplied by the primary or backup depot assigned to a ship-to-point, it can be shipped directly from the original supplier, or from a rival distributor, using a special expediting procedure. The average unit cost paid v^e when such recourse is used was also estimated.

Since the demand is stationary, a single engineering cycle constituted of one year of daily working periods needs to be considered, and evolutionary paths can be neglected. The main vulnerability sources to take into account are depots (S) and ship-to-points (D), i.e. $S = \{S, D\}$. Since the products distributed can be purchased from several alternative sources, and since their purchase price depends mainly on depots locations, supply sources are not considered as vulnerable, and they do not have to be modeled explicitly. The network is threatened mainly by natural disasters which are considered as a single multihazard, and it is sufficient to use US states as hazard zones. Exposure levels were specified bottom-up based on FEMA data, thus defining the sets of states $Z_g, g \in G$. These exposure levels are illustrated in **Figure 2**.

SCN Modeling

Two related supply chain modeling activities are required at this point: the elaboration of descriptive hazard models which can be used to generate plausible future scenarios, and the formulation of a normative design model which can be used to generate candidate SCN designs. The former involves the definition of stochastic processes to describe how multihazards occur in space and in time, and to specify incidents intensity and duration. Also, recovery functions based on intensity and time to recovery variables must be specified to quantify the impact of a hit on network resources and demand. Potential SCN modeling, on the other end, can involve the formulation of a tailor-made optimization model, or the use of generic SCN design software. These two SCN modeling activities are discussed in detail in the following sections.

Hazard Processes Modeling

This activity is initiated by modeling the arrival, intensity and duration of the multihazards $h \in H$ considered in the study. We assume that multihazards occur independently in hazard zones, and that the time between the occurrences of successive multihazards in a zone is characterized by a non-stationary stochastic arrival process depending on the evolutionary path considered. Note that these processes depend on the territory on which the SCN is deployed, but that they are independent of the SCN considered. Under evolutionary path $k \in K$, if an incident occurs in working period $\tau \in T^u$, then the time before the arrival of the next multihazard $h \in H$ in zone $z \in Z$ is a random variable $\lambda_{zk\tau}^h$ with cumulative distribution function $F_{zk\tau}^{\lambda^h}(.)$. In practice, catastrophe models often use Poisson processes to determine the number of extreme events that can occur in a given period (Banks, 2006). Accordingly, we consider that in most cases it is sufficient to assume that $F_{zk\tau}^{\lambda^h}(.)$ is an exponential distribution $Exp(\mu_{zk\tau}^h)$ with an expected time between multihazards $\mu_{zk\tau}^h$. Let $\phi_k^h(\mu_{z0}^h, \tau)$ be a function elaborated by experts, for evolutionary path k and multihazard h, to project the historical mean time between multihazards, μ_{z0}^h, estimated during the analysis activity, over the periods $\tau \in T^u$ of the planning horizon. Then, the required probability distributions are obtained simply by calculating $\mu_{zk\tau}^h = \phi_k^h(\mu_{z0}^h, \tau)$ for all h, z, k and τ.

The data provided by public or private sources such as FEMA, CRED, Swiss Re and Munich Re is often not sufficiently detailed to characterize the multihazards impact intensity and duration for each hazard zone. For this reason, the impact intensity and duration are usually modeled by exposure level. A hierarchical modeling approach based on conditional hazard zone hit probabilities, $p_{z/g}^h$, must then be used (Klibi and Martel, 2010b). These conditional probabilities are estimated subjectively based on public or constructed indexes. For example, for geopolitical failures the *Failed State Index* can be used, and for natural disasters an incident frequency index calculated from CRED data can be used. We assume that when a multihazard $h \in H$ occurs in a zone $z \in Z$, its duration (in working periods) and its intensity (in a generic measure such as the loss level or the casualty level per period) are characterized by two correlated random variables related to the zone exposure level $g(z) \in G_h$, namely: the impact intensity β_g^h, with cumulative distribution function $F_g^{\beta^h}(.)$ and the duration θ_g^h. The duration can be related to the intensity through incident *impact-duration functions* $\theta_g^h = f^h(\beta_g^h) + \varepsilon^h$, $h \in H$, estimated by regression, where ε^h is a Normally distributed error term. The impact distributions and the impact-duration functions are estimated from the incidents data.

The occurrence of an incident in a hazard zone does not necessarily result in a hit of all the SCN locations in that zone. When the hazard zones are large (countries or states), it is likely that only a part of the zone locations will be hit. Also, when considering the impact on product-markets, the SCN does not necessarily respond to all incidents. This leads to the estimation of

attenuation probabilities α_l^h which are conditional probabilities that location $l \in L$ is hit when a multihazard $h \in H$ occurs in zone $z(l)$. It is clear that these probabilities are related to the hazard zones granularity. Large zones lead to small attenuation probabilities, and vice versa. Attenuation probabilities can be estimated by experts for each SCN location, based on experience and data available.

When a location $l \in L$ in zone $z(l)$ is hit by a multihazard $h \in H$, the severity of the incident for the SCN is characterized on two correlated dimensions: a SCN resource/market impact intensity and the time to recovery (Sheffi, 2005). Clearly, these dimensions are related to the exogenous multihazard intensity and duration variables β_g^h and θ_g^h defined previously. However, the SCN impact severity must be expressed in units related to the capacity and demand of the vulnerability sources. It is assumed that the metrics used to characterize these two severity dimensions are the same for all the locations associated to a given vulnerability source, i.e. for all $l \in L_s$. Hence, for each vulnerability source $s \in S$, incident profiles must be specified for all locations $l \in L_s$, products $p \in P_s$ and multihazards $h \in H_s$. Damage on suppliers is typically assessed using an unfilled rate (% of material ordered during the incident not delivered) and the time required to restore supplies, whereas damage on production-distribution resources is usually assessed using a capacity loss rate and the time before production/distribution can resume. For vulnerability sources affecting demand, damage is usually assessed using an inflation or deflation rate expressing a demand surge or drop for a given period of time. Note that the evaluation of incidents severity may also be influenced by the state of the resources/partners associated to a vulnerability source.

Let ξ_l^h be a discrete random variable giving the time to recovery, in working periods, of location $l \in L$ when hit by a multihazard $h \in H_{s(l)}$. We assume that this time to recovery can be related to the multihazard duration $\theta_{g(l)}^h$ using an adequate translation function $\xi_l^h = q_{s(l)}^h(\theta_{g(l)}^h)$ specified for each vulnerability source $s \in S$ and multihazard $h \in H_s$. This function may be based on a proportion estimated from past instances or provided by experts. Consider a multihazard $h \in H$ hitting location $l \in L$ at the beginning of usage period $\tau' \in T^u$. Then, the impact of the hit lasts during periods $\tau = \tau',...,\tau'+\xi_l^h-1$. When a multihazard $h \in H$ hits a location l, its impact is not necessarily felt uniformly during the time to recovery ξ_l^h (Sheffi, 2005). Several phases are usually observed, depending on the nature of the multihazard and of the vulnerability source. For example, when a manufacturing plant is hit by a natural disaster, production capacity drops quickly during a first phase, then there may be a stagnation period while recovery measures are organized, and during a third phase the capacity is gradually restored. Such phase-dependent impacts can be characterized by defining discrete recovery functions $\boldsymbol{\rho} = r_s^h(\beta,\xi,\boldsymbol{\rho}), h \in H, s \in S$, where $\boldsymbol{\rho} = [\rho_{\tau'},...,\rho_{\tau'+\xi-1}]$ is a vector of capacity/demand amplification percentages for the ξ working periods affected by the multihazard. The $\rho_{\tau'},...,\rho_{\tau'+\xi-1}$ values

used as an argument in the function reflect amplification percentages before the hit and the function returns percentages after the hit. The use of these functions can be illustrated using the LTP case introduced previously. For this case, three types of recovery functions, associated respectively to customer inter-arrival times (q), to customer order sizes (o) and to depots capacity (a), must be defined: $\rho_{l\tau}^x = r^x(\beta_l, \xi_l, \rho_{l\tau}^x)$, $\tau = \tau', ..., \tau' + \xi_l - 1$, $x = q, o, a$. As illustrated in **Figure 11**, if the periods affected by the multihazard are not still recuperating from a previous incident, then the a priori percentages are $\rho_{l\tau}^x = 100\%$, $\forall x, l$, $\tau = \tau', ..., \tau' + \xi_l - 1$. The amplitude of the amplification depends on the multihazard impact intensity β_l. Using these recovery functions, the capacity and the demand can be calculated for specific periods and locations. For the order inter-arrival times and sizes, this gives rise to the perturbed random variables $q_{l\tau} = \rho_{l\tau}^q q_l$ and $o_{l\tau} = \rho_{l\tau}^o o_l$, $\tau = \tau', ..., \tau' + \xi_l - 1$, $l \in L^D$, and to their associated distributions functions $F_{l\tau}^q(.)$ and $F_{l\tau}^o(.)$. For the depots $l \in L^S$, this yield perturbed capacity levels $a_{l\tau} = a_l \rho_{l\tau}^a$, $\tau = \tau', ..., \tau' + \xi_l - 1$.
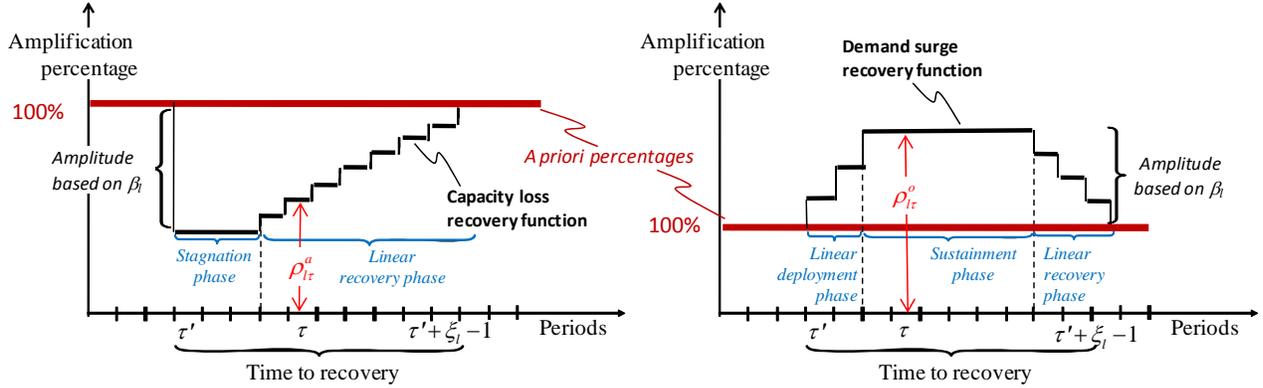
Figure 11. Recovery Function Examples for Depot $l \in L^S$ and Ship-to-Point $l \in L^D$

For the LTP case, two simplifying assumptions were made during the analysis: 1) there is no evolutionary trend, and consequently the index k can be dropped, 2) all hazards are grouped into a single multihazard, and thus the index h can be dropped. Under these assumptions, the hazard models can be simplified. The inter-arrival times for zone $z \in Z$ are characterized by the exponential random variable $\lambda_z \sim Exp_z(.)$, and the impact intensity by the uniform random variables $\beta_z \sim U_{g(z)}(.)$. We also assume that the duration translation functions $\xi_l = q_{s(l)}(\theta_{g(l)})$ are based simply on proportions estimated from past instances so that the impact-duration functions $\theta_g = f(\beta_g) + \varepsilon$ can be substituted back in the former to get simplified time to recovery functions for each vulnerability source, i.e. to get the relations $\xi_l = f_{s(l)}(\beta_{z(l)}) + \varepsilon_{s(l)}$, $\varepsilon_{s(l)} \sim N(0, \sigma_{s(l)}^\varepsilon)$. As we shall see, these hazard process models will be essential to generate plausible probabilistic scenarios $\omega \in \Omega^P$.

Potential SCN Modeling

The objective of this activity is to capture the essence of the SCN considered into an optimization model which can be used to generate good candidate designs. Since the future is uncer-

tain, this model should ideally be a multi-stage stochastic program (Birge and Louveaux, 1997) with sufficient details to anticipate the operations of the network adequately. Moreover, as indicated previously, some risk mitigation constructs should be incorporated in the model to obtain more resilient and robust SCN designs. Unfortunately, such models are extremely complex and difficult to solve. For this reason, complexity reduction measures are necessary. When design decisions are made on a rolling horizon basis, it is reasonable to use a multi-period two-stage stochastic program, which simplifies things considerably. Further complexity reduction is possible either by assuming that the future is known (to get a deterministic model), by considering resilience implicitly, and/or by using a crude approximation of the network operations to anticipate revenues and expenditures, which often leads to the use of location-allocation models (Klibi and Martel, 2009, Klibi *et al.*, 2010b). These simplified models may give good feasible designs which are, however, not necessarily optimal when evaluated with the performance metrics selected during the analysis activity. Two approaches can be utilized to model the network. One can exploit an existing generic model, such as the one proposed by Carle *et al.* (2010) which is implemented in the SCN design software SCN-STUDIO[1], or formulate a tailor-made model. The former may not provide a perfect fit for the company, but it requires no software development. The later may provide a better fit but it involves major software development efforts. The two approaches are discussed below.

Most of the SCN modeling construct presented in this paper are supported by SCN-STUDIO. Therefore, in order to formulate a design model, a company using such a tool must simply exploit these modeling constructs to represent its business context. With the software interfaces, the company specifies the product families and product-markets to use, the alternative market policies (offers) to consider, the transportation means and options available and their capabilities, the activity graph to apply and the associated recipes, the potential supply, production-distribution and demand locations available, the relationship between inter-location lanes and transportation means, the current and potential platforms for production-distribution sites and the activity they can support, as well as all relevant cost, price, resource consumption and capacity parameters. When some of these parameters are random variables, their probability distribution can also be defined. The user must then specify the planning horizon, the evolutionary trend functions, the scenario sample and the objective function to employ. Functionalities to take hazard processes into account are also under development. When all this information has been entered, SCN-STUDIO is able to automatically generate the multi-scenario MIP model to solve to obtain candidate SCN designs, and eventually to solve it using CPLEX.

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[1] SCN-STUDIO was developed during a joint research project involving CIRRELT, at Université Laval, Defence R&D Canada and Modellium Inc.

To illustrate the formulation of a tailor-made model, we use the LTP case discussed previously. Several stochastic programming models with different anticipation quality and resilience constructs, and therefore different complexity level, can be formulated for this problem (Klibi and Martel, 2009). We limit ourselves here to the presentation of a relatively simple stochastic location-allocation model with a multiple-sourcing strategy to increase the resilience of the designs obtained. More specifically, on a given day, we do not allow a customer order to be split but, on different days, orders do not have to be fulfilled from the same depot. Let $\underline{L}^S \subseteq L^S$ be the set of opened depots for a given SCN design. For a given scenario ω, on day τ, the depots capacity $a_{l\tau}(\omega)$, $l \in \underline{L}^S$, is known and the set of depots $\underline{L}^S$ can be partitioned into fully operational depots $\underline{L}^S_\tau(\omega) = \{l \,|\, a_{l\tau}(\omega) = a_l\}$ and partially operational depots $\underline{\tilde{L}}^S_\tau(\omega) = \{l \,|\, a_{l\tau}(\omega) < a_l\}$. Similarly, customer demand $d_{l\tau}(\omega)$, $l \in L^D$, is known and the set of ship-to-points $L^D_\tau(\omega) = \{l \,|\, d_{l\tau}(\omega) > 0\}$ can be specified. When a depot l is operational on day τ under scenario ω, additional capacity $\varphi_l a_l$, is available for use, where φ_l is a fixed proportion of regular daily capacity. As illustrated in **Figure 12**, the stochastic demand level and depot capacity on each day dictate the kind of response decisions made. When depot l is operational it serves its primary ship-to-point orders and it can process reassigned orders from other depots. When it is partially operational, however, it serves only a subset of its primary ship-to-point orders and the remaining ones are transferred. Thus, based on depots primary missions, revised daily assignment decisions $\underline{L}^D_{l\tau}(\omega)$, $l \in \underline{L}^S$, must be made to ensure that the depots capacity constraints $\sum_{l' \in \underline{L}^D_{l\tau}(\omega)} d_{l'\tau}(\omega) \le a_{l\tau}(\omega)$, $l \in \underline{L}^S$, are respected. Following these reassignments, each depot ships its assigned orders using a combination of transportation means depending on order sizes. Also, as indicated previously, if internal capacity is not sufficient on a given day, then some customer orders must be fulfilled from an expensive external supply source. This stochastic capacity-demand behaviour must be captured in the design model.
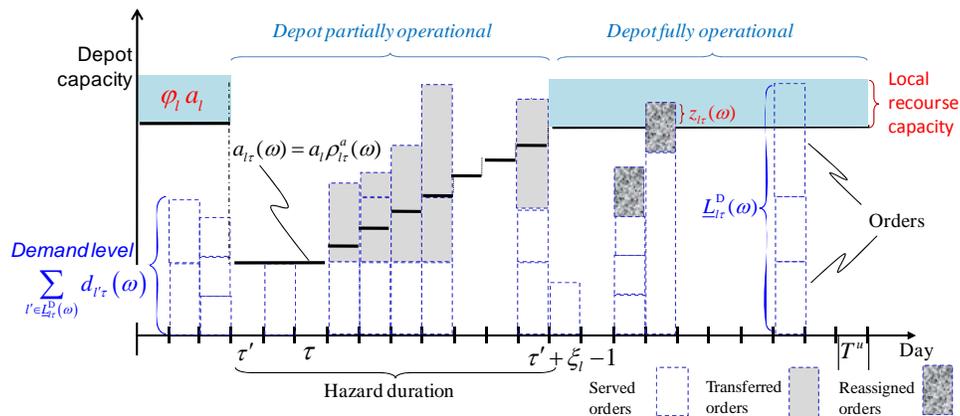
Figure 12. Capacity-Demand Behavior at Depot $l \in \underline{L}^S$ for a Given Scenario ω

Although several TL and LTL transportation options are available on a daily basis to ship orders to customers, in order to simplify the model, they can be aggregated in weekly depots to

ship-to-points flow variables with unit transportation costs $w_{ll'}$, $l \in L^S$, $l' \in L^D$. These unit costs are estimated by regression using daily historical data (Klibi *et al.*, 2010b). This aggregation could be done by summing daily demands and capacities to get weekly demands and capacities. This would assume however that an order arriving any day of the week could be supplied from the depot any day of the week, which is not realistic. Since demand processes are stationary, a better approach is to use period sampling, i.e. to consider one randomly selected day per week. The planning horizon is then constituted of a subset $\hat{T} \subset T^u$ of daily periods. Under this complexity reduction mechanism, ship-to-point demands for scenario ω are denoted $d_{lt}(\omega)$, $l \in L^D_t(\omega)$, $t \in \hat{T}$, and depot capacities $a_{lt}(\omega)$, $l \in L^S$, $t \in \hat{T}$.

To formulate the model, the following decision variables are required:

x_l : Binary variable equal to 1 if depot l is opened, and 0 otherwise

$x_{ll'}$: Binary variable equal to 1 if ship-to point l' can be supplied by depot l, and 0 otherwise

$F_{ll't}(\omega)$: Quantity of product supplied by depot l to ship-to point l' on day t under scenario ω

$z_{lt}(\omega)$: Recourse capacity needed at depot l on day t

$F^e_{l't}(\omega)$: Quantity of products supplied to ship-to-point l' by the external supply source on day t under scenario ω

The variables x_l and $x_{ll'}$ are first stage design variables (denoted collectively by the vector **x**), and $F_{ll't}(\omega)$, $z_{lt}(\omega)$, $F^e_{l't}(\omega)$ are second stage recourse variables depending on the prevailing scenario $\omega \in \Omega^P$. This leads to the following two-stage stochastic program with fixed recourse:

$$R = \max_{\mathbf{x}} \frac{|T^u|}{|\hat{T}|} \sum_{V=A,S} \pi^V \mathbf{E}_{\Omega^V|V} \left(R^u(\mathbf{x}, \omega) \right) - \sum_{l \in L^S} A_l x_l \tag{1}$$

subject to

$$x_{ll'} \leq x_l \qquad\qquad l \in L^S,\ l' \in L^D_l \tag{2}$$

$$x_l, x_{ll'} \in \{0,1\} \qquad\qquad l \in L^S,\ l' \in L^D_l \tag{3}$$

where

$$R^u(\mathbf{x}, \omega) = \max \sum_{t \in \hat{T}} \left[\sum_{l \in L^S} \left(\sum_{l' \in L^D_t(\omega) \cap L^D_l} [u_{l'} - v_l - w_{ll'}] F_{ll't}(\omega) - v^z_l z_{lt}(\omega) \right) + (u_{l'} - v^e) \sum_{l' \in L^D_t(\omega)} F^e_{l't}(\omega) \right] \tag{4}$$

subject to

$$\sum_{l \in L^S} F_{ll't}(\omega) + F^e_{l't}(\omega) = d_{l't}(\omega) \qquad\qquad l' \in L^D_t(\omega), t \in \hat{T}, \omega \in \Omega^P \tag{5}$$

$$F_{ll't}(\omega) \leq d_{l't}(\omega) x_{ll'} \qquad\qquad l \in L^S, l' \in L^D_t(\omega) \cap L^D_l, t \in \hat{T}, \omega \in \Omega^P \tag{6}$$

$$\sum_{l' \in L^D_{lt}(\omega)} F_{ll't}(\omega) \leq a_{lt}(\omega) + z_{lt}(\omega) \qquad\qquad l \in L^S, t \in \hat{T}, \omega \in \Omega^P \tag{7}$$

$$z_{lt}(\omega) \leq \varphi_l a_l, \ l \in L^S_t(\omega); \quad z_{lt}(\omega) \leq 0, \ l \in \tilde{L}^S_t(\omega) \qquad t \in \hat{T}, \omega \in \Omega^P \tag{8}$$

$$F_{ll't}(\omega) \geq 0, F^e_{l't}(\omega) \geq 0, z_{lt}(\omega) \geq 0 \qquad\qquad l \in L^S, l' \in L^D_t(\omega) \cap L^D_l, t \in \hat{T}, \omega \in \Omega^P \tag{9}$$

In the objective function (1) of the first stage program, $\mathbf{E}_{\Omega^V|V}(.)$ denotes the conditional expected value for acceptable-risk scenarios Ω^A or serious-risk scenarios Ω^S. The function $R^u(\mathbf{x}, \omega)$, gives the value of the second stage program (4-9) for a given design $\mathbf{x}$ and scenario ω. More specifically, it provides the net revenues generated during planning horizon $\hat{T}$. The expected net revenues are then multiplied in (1) by the horizon shrinking factor $|T^u|/|\hat{T}|$ to obtain an adequate approximation of the total expected profits. By using the probabilities π^A and π^S in the objective function (1), the total expected profit is obtained, which is adequate for a risk-neutral decision-maker. However, if the decision-maker is risk-averse, these probabilities need to be replaced by weights $\hat{\pi}_S > \pi^S$ and $\hat{\pi}_A = 1 - \hat{\pi}_S$ to give more importance to serious-risk scenarios (Klibi and Martel, 2009).

As it stands, this model cannot be solved because the set Ω^P contains an infinite number of scenarios. As we shall see, it can be solved relatively easily, however, if we restrict ourselves to a sample of randomly selected scenarios. Several other models were also proposed for facility location problems under uncertainty (Snyder and Daskin, 2005; Snyder, 2006).

Plausible Futures Generation

It should be clear by now that plausible future scenarios are a central element of our SCN reengineering methodology under uncertainty. We have seen how random business-as-usual events, high-impact disruptions and evolutionary paths can be modeled using stochastic processes. However, the joint impact of these events over the planning horizon must be represented in terms of a set of plausible future scenarios. In other words, the stochastic processes defined must be used to generate the sets of scenarios required to create and evaluate candidate designs. This can be done using standard Monte-Carlo techniques. To obtain a scenario $\omega \in \Omega^P$, we start by generating as many independent pseudorandom numbers, uniformly distributed in [0,1], as we have random events in our stochastic processes. Then, interpreting these numbers as cumulative probabilities, we use the inverse probability distributions of the random events to generate a scenario instance. When doing this, however, the hierarchical structure of the stochastic process models developed must be respected. In our context, the resulting scenario generation procedure obtained has five main steps:

1. An evolutionary path is randomly selected.
2. A chronological list T_z of all the multihazards arrival periods is constructed for every hazard zone $z \in Z$.
3. The intensity and duration of the disruptions considered are generated and used to calculate amplification factors with the recovery functions.
4. The amplification factors are used to calculate the working period's capacity and demand. The numeric value of hazard-independent random variables is also computed.

5. The working period quantities obtained are aggregated into planning period quantities.

The last step is required because the SCN design generation activity needs scenarios expressed in terms of planning periods $t \in \hat{T}$. The design evaluation phase however usually uses scenarios expressed in terms of working periods $\tau \in T^u$.

To illustrate the approach, for the LTP case, the Monte Carlo procedure required to generate depots capacity and ship-to-points demand values, for a scenario instance ω, is given in **Figure 13**. In the procedure, u denotes a pseudorandom number, $\Phi^{-1}(.)$ the inverse of the standardized Normal variate, and $T^u_t \subset T^u$ the set of days in planning period $t \in \hat{T}$. Note that Step 1) is skipped because, in the LTP case, evolutionary trends are not considered. This procedure can be used repeatedly to generate the scenario samples required in the next reengineering activities.

---

2) For all $z \in Z$, do:

    Using the distribution of λ_z, generate multihazard arrival moments $\mathrm{T}_z \subseteq T^u$

3)   Set $\rho^x_{l\tau} = 1$, $x = q,o,a$, $\forall l \in L_z$, $\tau \in T^u$

    For all $\tau' \in \mathrm{T}_z$, do:

        Compute $\beta_z = U^{-1}_{g(z)}(u)$

        For all $l \in L_z | u \le \alpha_l$, do:

            Compute $\xi_l = f_{s(l)}\left(\beta_{z(l)}\right) + \sigma^\varepsilon_{s(l)} \Phi^{-1}(u)$

            Compute $\rho^x_{l\tau} = r^x(\beta_{z(l)}, \xi_l, \rho^x_{l\tau})$, $\tau = \tau',...,\tau' + \xi_l - 1$, $x = q,o,a$

        End For

    End For

  End For

4) For all $l \in L^S$ and $\tau \in T^u$: Compute the daily capacity $a_{l\tau}(\omega) = a_l \rho^a_{l\tau}$

    For all $l \in L^D$, do:

        $\eta = 0$; $d_{l\tau}(\omega) = 0$, $\tau \in T^u$; $\tau = 1$; $F^q_{l\tau} = Exp_l$

        While $\eta \le |T^u|$, do:

            Compute the next order arrival time $\eta = \eta + F^{q^{-1}}_{l\tau}(u)$ and $\tau = \lceil \eta \rceil$

            Derive $F^q_{l\tau}$ from Exp_l and $\rho^q_{l\tau}$; Derive $F^o_{l\tau}$ from LN_l and $\rho^o_{l\tau}$

            Compute the daily demand $d_{l\tau}(\omega) = d_{l\tau}(\omega) + F^{o^{-1}}_{l\tau}(u)$

        End While

    End For

5) Select a day τ in the weeks T^u_t, $t \in \hat{T}$, to get $a_{lt}(\omega)$, $l \in L^S$, and $d_{lt}(\omega)$, $l \in L^D$

Figure 13. Monte Carlo Procedure for the Generation of a Scenario ω

SCN Designs Generation

During this activity, the design models previously formulated are solved to obtain candidate SCN designs. They are usually solved with commercial solvers, such as CPLEX (either directly or indirectly as is done when using a SCN design tool such as SCN-STUDIO), or with a tailor-

made heuristic method. When a stochastic programming model (such as (1-9)) is formulated, if the set of probabilistic scenarios Ω^P is large, then the model cannot be solved directly. The best that can be done is to solve it for some scenarios samples generated using the Monte-Carlo procedure discussed in the previous section. The approach involves the generation of several scenario samples, and the solution of the resulting sample average approximation (SAA) models (Shapiro, 2003), to get a set of candidate SCN designs. Given our partition of probabilistic scenarios in two subsets Ω^A and Ω^S, the idea is first to generate a large independent sample of M equiprobable scenarios $\Omega^M \subset \Omega$, and to partition it into the subset Ω^{M_A} of M_A acceptable-risk scenarios and the subset Ω^{M_S} of M_S serious-risk scenarios (using the hazard tolerance level κ, as illustrated in **Figure 3**). An estimate of the probabilities π^A and π^S is then given by $\bar{\pi}_A = M_A/M$ and $\bar{\pi}_S = 1 - \bar{\pi}_A$, and these estimates can be used to specify the value of the risk-aversion weights $\hat{\pi}_A$ and $\hat{\pi}_S$ to use in the SAA model. Second, a small sample Ω^{m_A} of m_A acceptable-risk scenarios is randomly selected in Ω^{M_A} and a small sample Ω^{m_S} of m_S serious-risk scenarios is randomly selected in Ω^{M_S} to get $\Omega^m = \Omega^{m_A} \cup \Omega^{m_S}$. This hierarchical sampling procedure provides equiprobable scenarios, with probability $1/m_A$ and $1/m_S$ respectively. These small scenario samples are then used to formulate a SAA model.

The approach can be illustrated with the LTP case discussed previously. The Monte Carlo procedure in **Figure 13** is first used to generate several samples of M scenarios, $\Omega_i^M, i = 1,...,I$. Then, proceeding as indicated in the previous paragraph, small scenario samples $\Omega_i^{m_A}, \Omega_i^{m_S}$, $i = 1,...,I$, of size m_A and m_S, respectively, are selected, and the weights $\hat{\pi}_A$ and $\hat{\pi}_S$ are specified. The SAA model to solve for a given scenario sample Ω_i^m is the following:

$$\max_{\mathbf{x}} \frac{|T^u|}{|\hat{T}|} \sum_{V=A,S} \frac{\hat{\pi}_V}{m_V} \sum_{\omega \in \Omega_i^{m_V}} \left(\sum_{t \in \hat{T}} \left[\sum_{l \in L^S} \left(\sum_{l' \in L_\tau^D(\omega) \cap L_l^D} [u_{l'} - v_l - w_{ll'}] F_{ll't}(\omega) - c_l^z z_{lt}(\omega) \right) \right. \right. \qquad SAA(\Omega_i^m)$$

$$\left. \left. + \left(u_{l'} - v^e \right) \sum_{l' \in L_t^D(\omega)} F_{l't}^e(\omega) \right] - \sum_{l \in L^S} A_l x_l \right) \qquad (10)$$

subject to

$$x_{ll'} \leq x_l \qquad\qquad l \in L^S, \ l' \in L_l^D \qquad\qquad (11)$$

$$\sum_{l \in L^S} F_{ll't}(\omega) + F_{l't}^e(\omega) = d_{l't}(\omega) \qquad\qquad l' \in L_t^D(\omega), t \in \hat{T}, \omega \in \Omega_i^m \qquad (12)$$

$$F_{ll't}(\omega) \leq d_{l't}(\omega) x_{ll'} \qquad\qquad l \in L^S, l' \in L_t^D(\omega) \cap L_l^D, t \in \hat{T}, \omega \in \Omega_i^m \qquad (13)$$

$$\sum_{l' \in L_{lt}^D(\omega)} F_{ll't}(\omega) \leq a_{lt}(\omega) + z_{lt}(\omega) \qquad\qquad l \in L^S, t \in \hat{T}, \omega \in \Omega_i^m \qquad (14)$$

$$z_{lt}(\omega) \leq \varphi_l a_l, \ l \in L_t^S(\omega); \quad z_{lt}(\omega) \leq 0, \ l \in \tilde{L}_t^S(\omega) \qquad t \in \hat{T}, \omega \in \Omega_i^m \qquad (15)$$

$$F_{ll't}(\omega) \geq 0, F_{l't}^e(\omega) \geq 0, z_{lt}(\omega) \geq 0 \qquad\qquad l \in L^S, l' \in L_t^D(\omega) \cap L_l^D, t \in \hat{T}, \omega \in \Omega_i^m \qquad (16)$$

$$x_l, x_{ll'} \in \{0,1\} \qquad\qquad l \in L^S, \ l' \in L_l^D \qquad\qquad (17)$$

Model $SAA(\Omega_i^m)$ is a mixed integer program and it can be solved relatively easily with recent commercial solvers, such as CPLEX-12. These solvers incorporate generic heuristics (such as the feasibility pump) to find good initial solutions and they are able to solve surprisingly large SCN design problems. Moreover, since our objective here is to generate good candidate designs, and since commercial solvers tend to take a lot of time to prove optimality after they found the optimal solution, larger optimality gap parameter values (say 0.01 instead of the default value of 0.0001) can be used to reduce computation times. Also, several heuristic methods were proposed in the literature to solve deterministic location-allocation problems (see Klibi *et al.* (2010a) for a review) and some of them can be extended relatively easily to solve stochastic versions of the problem.

Several instances of model $SAA(\Omega_i^m)$ were solved by Klibi and Martel (2010a) for realistic cases involving as many as 15 potential depots and 706 ship-to-points located in Northeast and Midwest US states. A one year planning horizon including 240 working days was considered, and the next day delivery requirement was implemented through a 400 miles limit on the distance between depots and ship-to points. Exponential order inter-arrival times were utilized with log-normal order quantities. Diverse cost and demand structures were examined for networks with different ship-to-point density and potential depots size. The models were generated with OPL Studio 6.1 and solved to optimality with CPLEX-11 on a 64 bits server with a 2.5 GHz Intel XEON processor and 16 GB of RAM. Samples of 1000 scenarios were used to estimate the probability $\bar{\pi}_A$ and $\bar{\pi}_S$ of acceptable and serious risk scenarios (a hit histogram is presented in **Figure 3** for one of these samples). Samples of 30 to 50 scenarios were embedded in the SAA models, and four replications were solved for each case ($I = 4$). The largest models included 883,766 variables and 905,351 constraints, and their optimal solution was found in 86 minutes, on average, with a 60 minutes standard deviation.

The SCN designs obtained with the I scenario samples generated are not necessarily all different. Also, additional candidate designs can be obtained by modifying the risk-aversion weights $\hat{\pi}_A$ and $\hat{\pi}_S$. The model as it stands tends to select two supply depots for each ship-to-point, i.e. to provide designs such that $\Sigma_{l \in L^S} x_{ll'} = 2, l' \in L^D$. The depot with the largest flow can then be considered as the primary supply depot $l_1^S(l')$ for ship-to-point $l' \in L^D$, and the other one as a backup depot $l_2^S(l')$. Nothing guarantees, however, that this will happen for all samples Ω_i^m, $i = 1, ..., I$, and constraints could be added in the model to impose this characteristic. Other model variants could also be used to generate alternative designs. Moreover, when inspecting the solutions obtained, the company may want to modify some designs to make them more attractive from their point of view. In any case, when this activity is completed, a number of candidate designs $\mathbf{x}^j$, $j = 1, ..., J$, are available and one of these designs must be selected.

Designs Evaluation and Selection

Since several complexity reduction mechanisms are typically used to generate candidate designs, the SCN designs $\mathbf{x}^j, j = 1,...,J$, are not necessarily optimal when considering all problem facets and all relevant performance measures. Consequently, candidate designs must be evaluated and compared based on operational response processes and performance metrics which are as close as possible to those of the company. Moreover, before changing its current SCN design, $\mathbf{x}^0$, the company will want to ensure that the new design provides significant value added. The status quo design $\mathbf{x}^0$ must therefore always be included in the list of designs to evaluate. Ideally, the designs $\mathbf{x}^j, j = 0,1,...,J$, should be evaluated for all plausible futures $\omega \in \Omega$. However, as indicated previously, this is not possible because there may be an infinite number of plausible scenarios. Again, the best that can be done is to perform the evaluation for a sample of scenarios. This sample must however be independent of the samples generated to get candidate designs, it must be much larger, and it must include worst-case scenarios in Ω^U. The value of a given design-scenario pair $(\mathbf{x}^j, \omega)$, is obtained by solving one or several models representing the response and SCN adaptation decisions taken over the planning horizon when the design considered is implemented. The set of scenario values thus obtained for a given design are used to evaluate performance measures. An adequate SCN design evaluation must be based on expected value, deviation and robustness measures, and it must take the decision-makers risk attitude into account. Based on these measures, classical multicriteria filtering and selection techniques are finally used to select the design to implement.

This design evaluation and selection approach can be illustrated with our LTP case. The Monte-Carlo procedure in **Figure 13** is first used to generate a large sample Ω^N of N scenarios, with $N \gg M$, and the sample is then partitioned into acceptable-risk scenarios Ω^{N_A} and serious-risk scenarios Ω^{N_S}, based again on the hazard tolerance level κ. From these samples, two moderate size subsets of scenarios are randomly selected to perform the design evaluation: a subset $\Omega^{n_A} \subset \Omega^{N_A}$ of n_A acceptable-risk scenarios, and a subset $\Omega^{n_S} \subset \Omega^{N_S}$ of n_S serious-risk scenarios. In order to obtain worst-case scenarios, a subset $\Omega^{n_W} \subset \Omega^{N_S}$ of tail scenarios is also selected in the distribution of the number of hits (see **Figure 3**). These scenarios are then taken as is, or modified manually by adding imaginative elements, to get the required set of worst-case scenarios Ω^{n_U}. Finally, an historical scenario ω^0 can also be defined from the customer orders and the disruptions which occurred during the last year. In practice, companies often want to know how candidate designs would have performed over the recent past.

The value of designs $\mathbf{x}^j, j = 0,1,...,J$, must then be obtained for scenarios $\Omega^n = \Omega^{n_A} \cup \Omega^{n_S} \cup \Omega^{n_U} \cup \{\omega^0\}$. If we were applying the standard SAA approach (Shapiro, 2003), the design evaluation would be done by solving the second stage program (4-9), with scenarios $\Omega^{n_A} \cup \Omega^{n_S}$, and the design with the highest expected value would be selected. However, since

the SAA model is based on several approximations, there is no reason to restrict ourselves to such a gross assessment. The evaluation of the designs should be based on a response optimization procedure as close as possible to the real operational processes. Also, to obtain $SAA(\Omega_i^m)$, we simplified the objective function, but when comparing the designs, there is no reason not to apply more adequate performance evaluation measures.

The assignment-transportation procedure described in **Figure 14**, can be utilized to calculate the net revenues $\hat{R}^u(\mathbf{x}, \omega)$ generated over the planning horizon for a given SCN design $\mathbf{x}$ under a given scenarios ω. This procedure is based on the response policy of the company specified during the analysis activity. In the procedure, $R_{l\tau}(\mathbf{x}, \omega)$ denotes the daily revenues of opened depot $l \in \underline{L}^S$, $C_\tau^{\mathbf{z}}(\mathbf{x}, \omega)$ the network loss on day τ for external recourses, and L is a priority list ranking ship-to-points $l \in L^D$ in decreasing order of their importance. On a given day τ, based on the set $L_\tau^D(\omega)$ of ordering customers, list L is used to assign the most important customers to their primary depot $l_1^S(l')$ and to transfer the remaining orders to the backup depot $l_2^S(l')$ or to an external supply source. Note that if the design $\mathbf{x}$ considered does not specify the backup depot explicitly, then $l_2^S(l')$ is specified using a distance or flow based rule. In the second part of the procedure, a transportation problem must be solved for each day and for each depot $l \in \underline{L}^S$ which are opened in design $\mathbf{x}$. This problem is solved in two steps: 1) for orders that are larger than a truckload b^F, a decision is made to ship as much as possible in FTL; 2) a routing algorithm is used to construct delivery routes for the residual order quantities. The routing algorithm employed should be as close as possible to the procedure used in practice by the company. The **UserResponse** procedure yields the net SCN revenues associate to day to day operations during the planning horizon. In order to obtain the value added by the SCN the fixed depots costs must also be taken into account. The value of the designs for each scenario is thus calculated as follows:

$$\hat{R}(\mathbf{x}^j, \omega) = \hat{R}^u(\mathbf{x}^j, \omega) - \sum_{l \in \underline{L}^S} A_l(x_l^j), j = 0, 1, ..., J, \ \omega \in \Omega^n \tag{18}$$

The design values by scenario provided by (18) can finally be used to compute the selected performance measures. For the LTP case, the following four measures would be relevant. The expected value $\bar{R}(\mathbf{x}^j)$ of a design $\mathbf{x}^j$ is provided by:

$$\bar{R}(\mathbf{x}^j) = \sum_{V=A,S} \bar{\pi}_V \bar{R}_V(\mathbf{x}^j); \qquad \bar{R}_V(\mathbf{x}^j) = \frac{1}{n_V} \sum_{\omega \in \Omega^{n_V}} \hat{R}(\mathbf{x}^j, \omega), \ V = A, S \tag{19}$$

where $\bar{R}_A(\mathbf{x}^j)$ and $\bar{R}_S(\mathbf{x}^j)$ are conditional expected values for acceptable and serious risk scenarios, respectively. Since downside deviations from mean returns are undesirable, an adequate variability measure to assess a design $\mathbf{x}^j$ is the mean-semideviation $MSD(\mathbf{x}^j)$ given by:

$$MSD(\mathbf{x}^j) = \sum_{V=A,S} \overline{\pi}_V MSD_V(\mathbf{x}^j) \qquad MSD_V(\mathbf{x}^j) = \frac{1}{n_V} \sum_{\omega \in \Omega^{nV}} \max\left[\left(\overline{R}_V(\mathbf{x}^j) - \hat{R}(\mathbf{x}^j,\omega)\right);0\right] \quad (20)$$
$$, V = A, S$$

where $MSD_A(\mathbf{x}^j)$ and $MSD_S(\mathbf{x}^j)$ are conditional mean-semideviations for acceptable and serious risk scenarios, respectively. Worst-case scenarios, can be used to evaluate an absolute robustness measure proposed by Kouvelis and Yu (1997). For design $\mathbf{x}^j$ this measures the minimum return $\overline{R}_U(\mathbf{x}^j)$ under all worst case scenarios, calculated as follows:

$$\overline{R}_U(\mathbf{x}^j) = \min_{\omega \in \Omega^{nU}} \left\{\hat{R}(\mathbf{x}^j,\omega)\right\} \tag{21}$$

UserResponse $(\mathbf{x},(l'(p),l \in L^D),(L_\tau^D(\omega),\tau \in T^u),L\,;\hat{R}^u(\mathbf{x},\omega))$

For all $\tau \in T^u$, do:

  Assign orders to depots

  For all $l' \in L_\tau^D(\omega)$, in order of the priority in L, do

      If capacity available at $l_1^S(l')$ then assign ship-to point l' to depot $l_1^S(l')$

      Else, If capacity available at $l_2^S(l')$ then assign ship-to point l' to depot $l_2^S(l')$

      Else use the external supply source to serve l'

  End do

  Compute depot revenues and expenditures

   For all $l \in \underline{L}^S$, do

     Solve the day τ *transportation problem* to get the transportation costs $\hat{C}_{l\tau}^u(\omega)$

     Compute depot l net revenues

$$\hat{R}_{l\tau}(\omega) = \sum_{l' \in \underline{L}_{l\tau}^D(\omega)} \left(\left[(u_{l'} - v_l)d_{l'\tau}(\omega)\right] - v_l^z z_{l\tau}(\omega)\right) - \hat{C}_{l\tau}^u(\omega)$$

   End do

  Compute the transportation costs $\hat{C}_{0\tau}^u(\omega)$ for the external supply source

End do

Compute the SCN design net revenues $\hat{R}^u(\mathbf{x},\omega) = \sum_{\tau \in T^u}\left(\sum_{l \in \underline{L}^S}\hat{R}_{l\tau}(\omega) - \hat{C}_{0\tau}^u(\omega)\right)$

Figure 14. User Response Procedure

Measures (19)-(21) provide the basis for a multi-criteria evaluation of the designs considered. The value of the designs $\hat{R}(\mathbf{x}^j,\omega^0)$ for the historical scenario ω^0 can also be taken into account. Any multicriteria analysis method can then be used to eliminate dominated designs and to rank non-dominated designs. A compound utility measure is also provided by the following expression:

$$R(\mathbf{x}^j) = (1-\psi)\sum_{V=A,S}\hat{\pi}_V\left(\overline{R}_V(\mathbf{x}^j) + \gamma_V MSD_V(\mathbf{x}^j)\right) + \psi\overline{R}_U(\mathbf{x}^j) \tag{22}$$

where $\gamma_V \in [0,1]$, $V = A, S$, are variability aversion weights for acceptable and serious risk scenarios, and where $\psi \in [0,1]$ is an extreme event aversion weight. Using this approach, the best design can be selected for implementation. Note that the computational efforts associated to this evaluation and selection activity is much smaller than for the design generation phase. For the LTP, when a standard SAA approach is applied, calculating the value of a design $\mathbf{x}^j$ with (18) involves the solution of the second stage program (4-9) for one scenario $\omega \in \Omega^n$ at the time, and this program can be separated per day. The resulting linear programs are easily solved with CPLEX. When the approach suggested here is applied, the user response problem becomes even simpler because it decomposes per depot.

4. Conclusion

This paper presents a relatively generic supply chain network reengineering methodology for businesses operating in an uncertain environment. A particular attention was given to the modeling of high impact disruptive events. General guidelines were given and, to illustrate the approach, more detailed explanations were provided for the case of the location-transportation problem under uncertainty. Although the methodology is comprehensive, that is, it considers strategic location, capacity, sourcing, transportation and marketing decisions in an integrated manner, these decisions are rarely reconsider all together in practice. Doing so, would give rise to huge projects with extremely difficult models to solve. At a given point in time, a company seeks rather to reoptimize only a subset of these decisions, which yield manageable projects and models. The methodology should therefore be perceived as a continuous improvement process.

The objective pursued is to provide sustainable SCN value creation by seeking designs which are both effective and robust. The methodology evaluates robustness through a high-quality anticipation of user decisions, for a sample of adequately selected plausible future scenarios. The risk attitude of the decision maker is also considered. Complementary work performed to test the methodology (Klibi and Martel, 2009; Klibi *et al.*, 2010b) indicates that it offers a judicious accuracy-solvability trade-off. The approach is also the backbone of a commercial SCN design tool (SCN-STUDIO) which was developed to support businesses in their effort to improve their supply chains.

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