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July 2009

CIRRELT-2009-28

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The Design of Effective and Robust Supply Chain Networks

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Abstract. This paper provides a methodology for Supply Chain Network (SCN) design under uncertainty. The problem is initially defined as a two level organizational decision process: the design decisions must be made here and now, but the SCN can be used only after an implementation period. During a multistage planning horizon a set of user response decisions and a set of planned structural adaptation decisions must be anticipated. The methodology recognizes three event types to characterize the future SCN environment: random, hazardous and deep uncertainty events. At the design time, future environments are anticipated through a scenario planning approach. Scenario samples generation allows approximating the design model to be solved with a sample average approximation program in order to produce a set of alternative designs. A design evaluation approach is then applied to select the most effective and robust SCN among this set and the status quo design.

Keywords. Supply Chain Network (SCN) design, uncertainty, robustness, anticipation, scenario planning, network disruptions, multihazard, stochastic programming.

Acknowledgements. This research was supported in part by Natural Sciences and Engineering Research Council of Canada (NSERC) grant no DNDPJ 335078-05, by Defence R&D Canada and by Modellium Inc.

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Dépôt légal – Bibliothèque et Archives nationales du Québec,
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Introduction

Supply Chain Network (SCN) design involves strategic decisions on the number, location, capacity and mission of the supply, production and distribution facilities of a supply chain in order to provide goods to a predetermined, but possibly evolving, customer base. Location models have been studied extensively in the literature under deterministic, dynamic and stochastic environments. Detailed reviews of location models are found in Owen and Daskin (1998) and Klose and Drexl (2005). Location models based on stochastic optimization (Birge and Louveaux, 1997; Snyder and Daskin, 2006) and robust optimization approaches (Kouvelis and Yu, 1997) were also proposed to take uncertainty into account. A review of location models under uncertainty is found in Snyder (2006). When classical location models are extended to design SCNs, other strategic decisions on sourcing, capacity acquisition, technology selection and market policies must be considered. The problem then is much more complex: the number of echelon in the network increases, objectives become heterogeneous, new complex constraints, to deal with international issues for example, are needed and the environment uncertainty increases. Management's ultimate goal is to maximize the effectiveness and competitiveness of the SCN. The predominant approach to solve these problems has been to use deterministic mathematical programming models with appropriate sensitivity analysis and scenario analysis. An integrated deterministic modeling framework incorporating most of the aspects of the problem studied to date is presented in Martel (2005).

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 (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 and hurricane Katrina, companies are aware that they should prepare for the next disaster, but in reality only a few do (Lee, 2004; Sheffi, 2005). At a time when management efforts strive to make supply chains as lean as possible such events may have serious impacts on company performances (Hendricks and Singhal, 2005). Clearly, this type of event should be taken into account in SCN design models. Moreover, in most real life projects, one has to compare the design proposed with the status quo network. This is often done by calculating the economic value of the two solutions with the objective function of the mathematical model used to obtain the proposed design, which is inadequate. It is then legitimate for management to question the precision and validity of such results. As far as we know, this question has not been addressed explicitly in the SCN literature.

A few authors have proposed stochastic linear programming (SLP) models (Pomper, 1976; Eppen *et al.*, 1989; Santoso *et al.*, 2005; Vila *et al.*, 2007) and robust optimization (RO) models

(Gutierrez *et al.,* 1995; Snyder *et al.*, 2006) to deal with environment uncertainty in SCN design. The models proposed however apply either to simplified location problems, or they consider only certain types of uncertainties, which compromise their solution robustness for real life problems. No comprehensive approach dealing with all the issues raised above currently exist. A critical review of major drawbacks and missing links in the current SCN design literature is found in Klibi *et al.* (2009a).

This paper proposes a SCN design methodology taking into account the various types of uncertainties that may affect a supply chain. A scenario based solution approach to design and evaluate SCNs under uncertainty is also proposed. The paper is organized as follows. Section 2 presents the SCN design methodology. It also proposes an approach to take high-impact disruptions into account in SCN design models. Section 3 proposes a generic solution approach to obtain robust value-creating SCN designs. Finally, conclusions and future research directions are provided.

SCN Design Methodology

Decision problem structure

SCN design problems deal with strategic decisions such as facility location, technology selection, capacity acquisition and deployment issues that are the responsibility of top management. At that level, a major preoccupation is the long term financing of the investments required, the expected return on these investments, risk management and, more generally, the impact of the SCN design decisions on the value of the firm, in a business context, or on the effectiveness with which the organization can accomplish its mission, in other contexts (government, military, NGOs…). However, design decisions impose resource availability and utilization constraints on the users of the SCN which, through their daily supply, production and distribution actions, in response to customer demands, determine the return that will be obtained from the investment. Note that although much of the following discussion is cast in a business context, the methodology proposed applies as well to non-business contexts.

Clearly, design decisions cannot be made without anticipating how the users will use the SCN to respond to daily events. The timing of the decisions made at the design and user response levels must also be taken into account. At the beginning of the planning horizon, SCN design decisions are made and after an implementation period the network designed or reengineered becomes available for use during several *usage* periods. During these usage periods, users serve customers, and react to disruptions, on an ongoing basis with the SCN designed. Although events occur continuously, we assume that the users make daily or weekly decisions, and thus that it is sufficient to observe the environment at the beginning of discrete *working* periods $\tau \in T^u$. Furthermore, additional design decisions will be taken in time to adapt the SCN to its environment, which leads to replications of the design and response *planning cycle* along the planning horizon considered. This gives rise to the multi-stage decision process illustrated in **Figure 1** for two planning cycles. However, in a rolling horizon framework, the only decisions implemented when the problem is solved at the beginning of the horizon are the first design decisions. Subsequent design decisions can be considered as future opportunities to adapt the network to its environment. During the planning horizon some disruptions may also affect the SCN. Unfortunately, at the beginning of the horizon, the future is not known. The best that can be done is to anticipate, with the information currently available, what the users and the designer will subsequently do to respond to the business environment that will prevail and to adapt the structure of the SCN. In order to avoid any ambiguity, in what follows, we use the expressions *design decision* only for the decisions to be implemented at the beginning of the horizon. Subsequent design decisions are referred to as *structural adaptation decisions*.

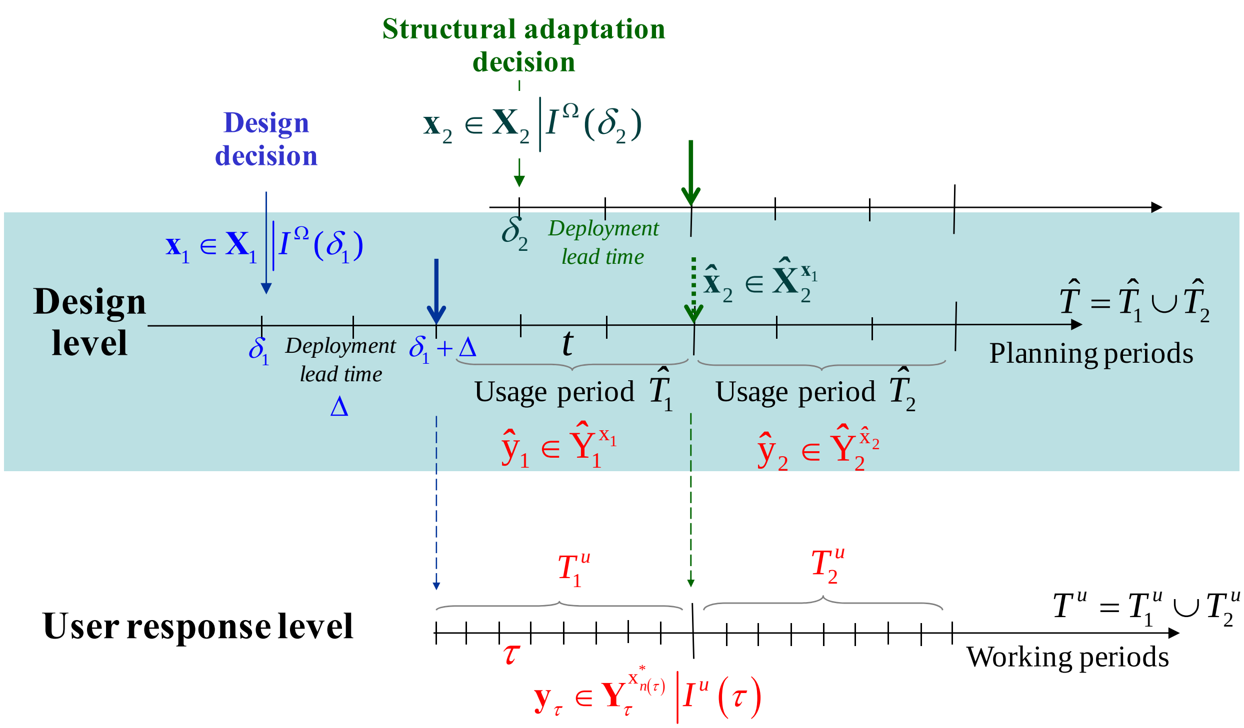

Figure 1. Decision Time Hierarchy for Two Planning Cycles

This paper proposes a SCN design methodology based on the explicit modeling of the design and user response levels over a multi-stage planning horizon. Each level is described by a decision model depending on a, possibly multi-criterion, preference structure C, on a decision space (**X** for the design level and **Y** for the user response level), and on the information available I at the time a decision is made. It is assumed however that the two levels consider themselves as part of a team (i.e. they do not have an antagonistic behaviour) and that the information asymmetry is due mainly to the fact that the decisions are not made at the same time. The anticipation pertains, first, to the response of the user to short term events within the network provided by the design level for each planning cycle (stage). In addition, the anticipation covers the SCN structural adaptation decisions for future planning cycles. This leads to the formulation of an anticipated *adaptation-response model*. A perfect anticipation is not possible, however. The response and design models could be used in the anticipation but, because of the decision time lag, the information cannot be the same. In most cases, the anticipated adaptation-response model is based on aggregate information and on simplified response and design models. It must be realized that the anticipation used has a major impact on the quality of the SCN designed. The role of anticipations in SCN design is studied in Klibi *et al.* (2009b). They investigate the impact of various response anticipation sub-models on SCN design quality, and they show that there is an (anticipation accuracy, model solvability) trade-off to consider in order to obtain good SCN design models.

As illustrated in **Figure 1**, we assume in this text that the planning horizon considered covers a set N of planning cycles also referred to as decision stages. At the user response level, for stage $n \in N$, decisions are made each working period $\tau \in T_n^u$ (days or weeks). At the design level, these working periods are usually aggregated into quarterly or yearly planning periods $t \in \hat{T}_n$. Each planning cycle $n \in N$ starts with a design (adaptation) decision at date δ_n. A known implementation lead time of Δ planning periods is then incurred before the new design is available. The planning cycle includes the set of planning periods $t \in \hat{T}_n$ defined to cover the working periods $\tau \in T_n^u$. The complete planning horizon considered is thus defined by $\hat{T} = \hat{T}_1 \cup \hat{T}_2 ... \cup \hat{T}_{|N|}$ at the design level or by $T^u = T_1^u \cup T_2^u ... \cup T_{|N|}^u$ at the user response level. In what follows, $n(t)$ is used to denote the planning cycle n containing period t.

At the beginning of each working period $\tau \in T^u$, when the user has to make his decisions, the information available $I^u(\tau)$ is almost perfect, but at time δ_1 design decisions are made under uncertainty. The information available at time δ_n is denoted by $I^{\Omega}(\delta_n)$ and we assume that it relates to a set Ω of plausible future scenarios. The fundamental structure of this strategic decision problem is presented in **Figure 2**. The formulation used is based on the generic distributed decision-making framework proposed by Schneeweiss (2003). It is assumed that design decisions are made on a rolling horizon basis.

In the figure, the hat ‘ ^ ’ is used to indicate terms in the anticipation, and $\mathbf{R}\,\{...|I\}$ is a generalized future return measure depending on the nature of the information available I. The superscripts d and u are used to denote the design and user response levels, respectively. At the design level, $\mathbf{x}_1$ is the vector of the location, technology, capacity, mission and resilience strategy decisions made at time δ_1, $\mathbf{X}_1$ is the feasible design space for this decision vector, and $\mathbf{x}_1^*$ is the design selected for implementation. C^d and $\hat{C}^{du}$ are respectively the *private* criterion and the *top-down* criterion of the design model. The former captures mainly investment costs. The later is the part of the design-criterion taking future response decisions and structural adaptation decisions into account; it captures the revenues and expenses generated by using the SCN and the additional investment costs necessary to adapt the SCN during the planning horizon. The anticipated design criterion $\hat{C}^d$ is used to evaluate the structural adaptation decision vector $\hat{\mathbf{x}}_n(\omega)$ under scenario $\omega \in \Omega$, and $\hat{\mathbf{X}}_n^{\mathbf{x}_{n-1}}(\omega)$ is the feasible structural adaptation decisions space for stage n. Note that the later depends on the state of the system at the beginning of cycle n, i.e. on the design decisions of the previous period.

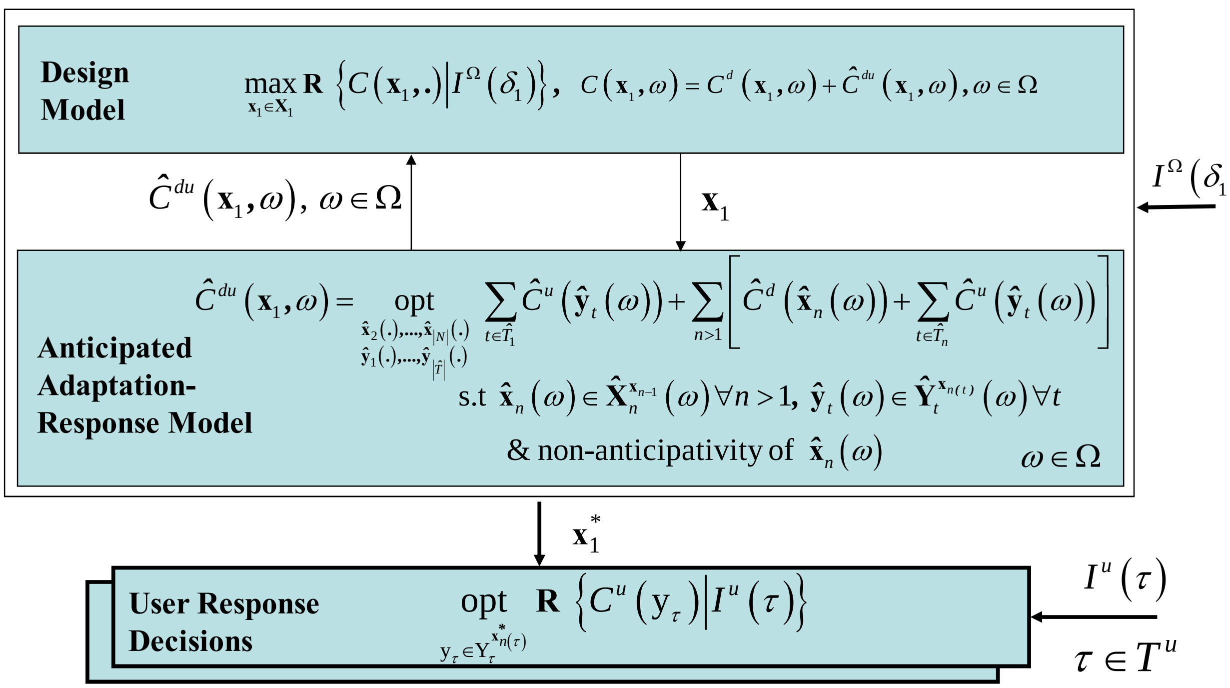

Figure 2. Strategic Decision Framework

At the user response level, $\mathbf{y}_\tau$ is the vector of tactical, operational and/or recourse procurement, production, warehousing and transportation decisions made for each working period $\tau \in T_n^u$. The user model return measure $\mathbf{R}\{C^u(y_\tau) | I^u(\tau)\}$ depends on the nature of the information available $I^u(\tau)$. At the design level, all these tactical and response decisions can usually not be considered explicitly: they are replaced by aggregate surrogate decision vectors $\hat{\mathbf{y}}_t(\omega)$, with value depending on the scenario $\omega \in \Omega$, for each planning periods $t \in \hat{T}$. The anticipated response criterion $\hat{C}^u$ and decision space $\hat{\mathbf{Y}}_t^{\mathbf{x}_{n(t)}}(\omega)$ are constructed conceptually from the user response level model and/or statistically from past behaviour observations. The adaptation-response model typically involves aggregations over products, customers, means of transportation and working periods. However, these anticipation decisions cannot be implemented and are only used to anticipate the revenues and expenses of the adaptation-response model. For a given design $\mathbf{x}_1 \in \mathbf{X}_1$ and a given scenario $\omega \in \Omega$, the anticipated adaptation-response model optimizes the value of surrogate response decisions and structural adaptation decisions over the planning horizon. In addition, *non-anticipativity* constraints must be added to ensure that the decisions $\hat{\mathbf{x}}_n(\omega)$ are identical for all the scenarios ω incorporating the same events for the previous periods.

In the design model, the future value of design $\mathbf{x}_1$ is assessed using a return measure $\mathbf{R}\left\{C(\mathbf{x}_1,\boldsymbol{.}) \middle| I^{\Omega}(\delta_1)\right\}$ taking all the scenarios $\omega \in \Omega$ into account and which, as we shall see, may be defined to reflect both expected value and aversion to risk. This return measure would also normally incorporate a discount factor to take the timing of C into account.

Characterization of the information available

A supply network must be designed to cope with its future environment, but at the point in time when it is engineered (or reengineered) the future is not known with certainty. 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. Randomness is characterized by random variables related to business as usual operations, hazard by low probability unusual situations with a high impact and deep uncertainty by the lack of any information to assess the probability of plausible future events. For hazards, it may be very difficult to obtain sufficient data to assess objective probabilities and subjective probabilities must often be used. A detailed discussion of the relevance of these three types of uncertainties for supply chain design is found in Klibi *et al.* (2009a).

During a planning horizon, the SCN evolves under varying environments. An *environment* is defined as the internal and external conditions under which the SCN operates during a given period of time. The future is considered at the design level by specifying possible sequences of environments over the planning periods $t \in \hat{T}$. Each possible sequence of environments defines a *scenario*. An *event* is a measurable (i.e. having observable consequences) factor or incident influencing the business environment during a given time period. An event is defined over an adjacent subset of planning periods in $\hat{T}$. The environment of planning period t is a compound event, i.e. the result of all the events occurring during period t. From our characterization of uncertainty, it is seen that three types of events shape SCN environments: random, hazardous and deeply uncertain events.

Random events are assumed to be defined over a single period $t \in \hat{T}$, and they describe factors with a probability of occurrence which 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 the SCN. These events include the degenerate case of *certain events* that occur when perfect information exists.

Hazardous events describe factors or incidents affecting a number of adjacent planning periods in $\hat{T}$ and creating 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 hazards affecting a geographical region, such as earthquakes, floods, windstorms, volcanic eruptions, droughts, forest fires, heat waves, freezes and cold waves. 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 planning periods in $\hat{T}$ 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, like the 9/11 WTC attack and the SARS epidemic, have lead to major business failures. Lempert *et al.* (2006) suggest the use of narrative scenarios in deep uncertainty situations and show how to use these scenarios to enhance solution robustness.

The events matrix presented in **Figure 3** is a crossover between our information-based classification of events and their expected severity. Light zones correspond to random events having normal impacts on SCNs. As seen in the introduction, several deterministic models and a few stochastic programming models were proposed in the literature to deal with SCN design problems under these types of events. Dark zones correspond to hazardous and deeply uncertain events. As indicated previously, some robust optimization approaches were proposed to deal with simple location problems under these types of events. Our aim here is to propose an integrated SCN design methodology to take all these types of events into account. The methodology proposed is based on recent work in stochastic programming (Shapiro, 2007), catastrophe modeling (Grossi and Kunreuther, 2005), scenarios planning (Van der Heijden, 2005) and risk analysis (Haimes, 2004). It builds on the fact that in all these modeling approaches, the information available on the future can be presented in the form of a set of scenarios about how the future may unfold.

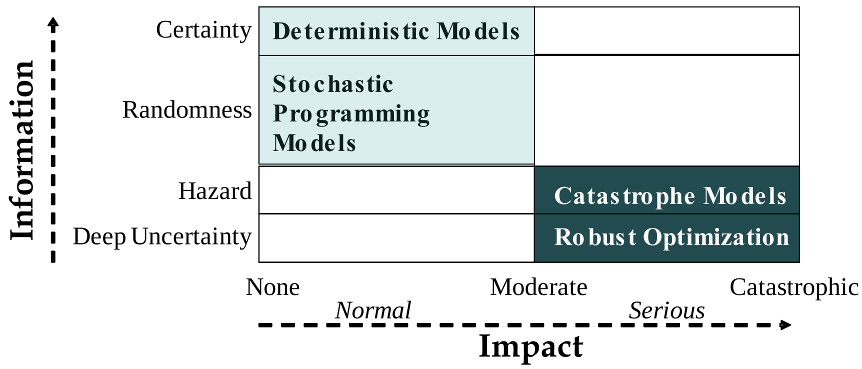

Figure 3. Events Matrix

From our previous definitions, it is clear that a scenario is a compound event. Each scenario is the result of the juxtaposition of one or more event types that shape the environment of SCNs. All scenarios include random events associated to business-as-usual conditions, but they do not necessarily include the hazardous or deeply uncertain events associated to the SCN threats discussed previously. Hereafter, totally destructive events causing irreversible damages to an entire business are excluded from the analysis. Also, in what follows, in order to analyse the various sources of risk properly, it is necessary to partition the set of scenarios Ω into two mutually exclusive and collectively exhaustive subsets: Ω^P including all *probabilistic* scenarios without deeply uncertain events (*P*-scenarios), and Ω^U including all other scenarios (*U*-scenarios). In principle, it should be possible to evaluate the probability $p(\omega)$ of scenarios $\omega \in \Omega^P$. However, the probability of *U*-scenarios cannot be evaluated. A conceptual representation of the scenarios tree thus obtained, and of its relationship with SCN decisions, is provided in **Figure 4**. Each path in this tree correspond to a scenario $\omega \in \Omega$.

Businesses and organizations operate in a complex world and, when looking far away, it cannot be assumed that the future will unfold in the tracks of the past. When developing their strategies, 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 **Figure 4** must consider such evolutionary paths. The scenarios in Ω are possible realizations of a set of underlying stochastic processes with known (for *P*-scenarios) or unknown (for *U*-scenarios) 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 $k \in K$.

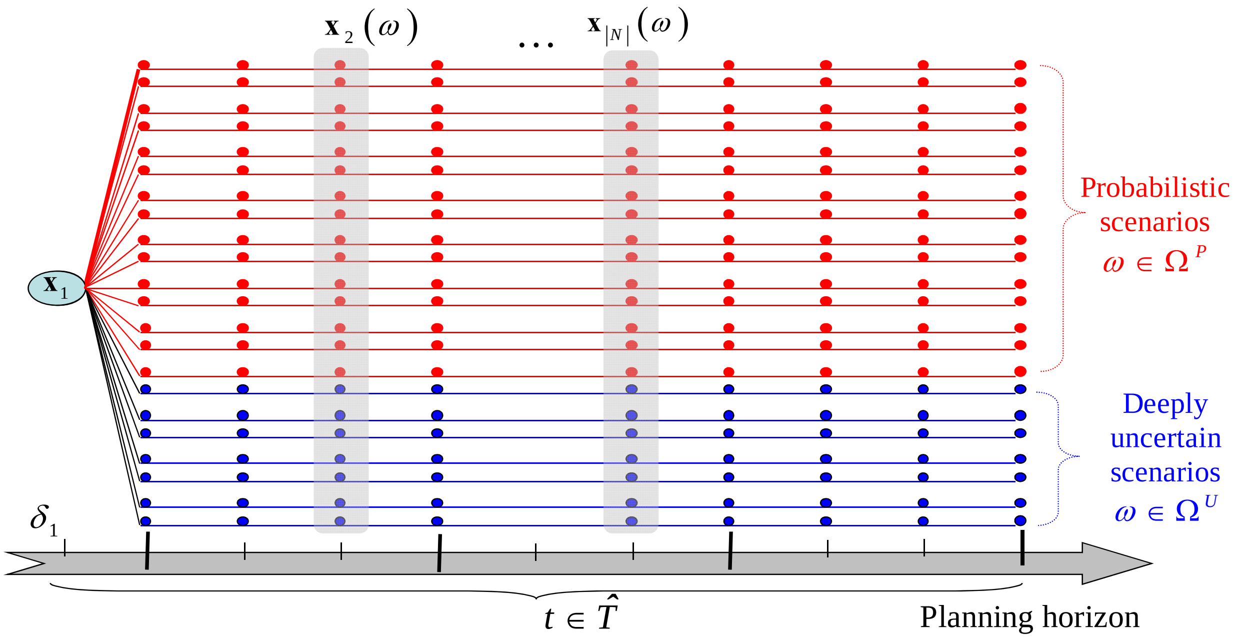

Figure 4. Scenarios Tree for the Planning Horizon

SCN Risk Analysis

Supply chain networks are usually geographically dispersed across regions and countries which increase their risk exposure and, in order to design robust SCNs, the impact of random, hazardous and deeply uncertain events must be taken into account. Using historical data, classical forecasting and statistical analysis methods can be used to estimate the probability distributions associated to random events. However, the case of hazards and deep uncertainty deserves further analysis. The disruptions which may affect a supply chain can take several forms and it is important to find a practical way of taking them into account without getting lost into a maze of possible incident types. This can be done by classifying hazards into a small number of meta-events with generic impacts on SCN resources (*multihazards*) and, by considering deep uncertainty through the use of imaginative scenarios. To embed this in our SCN design methodology, we must provide an answer to the three fundamental questions associated to risk analysis: 1) What can go wrong? 2) What are the consequences? 3) What is the likelihood of that happening? For deep uncertainty events, only the two first questions can be partially answered. For hazards, this leads to a three phase approach to model SCN exposures. It combines concepts from catastrophe analysis (Haimes, 2004; Grossi and Kunreuther, 2005; Banks, 2006) and SCN vulnerability analysis (Helferich and Cook., 2002; Kleindorfer and Saad, 2005; Sheffi, 2005; Craighead *et al.*, 2007, Wagner and Bode, 2008).

The next paragraphs describe the three phases of the SCN hazard modeling approach proposed. The role of each of these phases is the following:

1) *Characterization of multihazards and vulnerability sources*. The SCN vulnerability sources to take into account in the study are identified and related to relevant multihazards to specify threat domains. The territory over which the network is deployed is partitioned into hazard zones, which are related to exposure levels or regions. When the phase is completed, each network location is associated to a vulnerability source, a hazard zone and an exposure level.

2) *Modeling of multihazard processes*. A compound stochastic process is defined to describe how multihazards occur in space and in time, and to specify incident's intensity and duration. This phase is independent of the SCN considered. We assume that each incident occurs in a hazard zone at the beginning of a working period. The impact intensity and duration variables are however associated to exposure levels.

3) *Modeling the impact of hits on the SCN*. 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 are defined to reflect hits likelihood. When a location is hit, the impact on the network capacity and demand is modelled using recovery functions based on intensity and time to recovery variables.

In what follows the approach is described in generic terms and examples are given to illustrate particular cases.

Multihazards and vulnerability sources

To perform its activities the SCN exploits internal resources, it does business with SC partners, and it uses public infrastructures. Examples of typical resources, partners and infrastructures are given in **Figure 5**. These resources/partners are associated to specific geographical locations. Moreover, when modeling a SCN, some of these locations may be aggregated into geographical zones with a computable centroid. For example, in a business context, ship-to points are usually aggregated into demand zones and, in a military context, demand is naturally associated to regions where conflicts of various types may develop. Let L be the set of all the SCN locations considered. When an extreme event occurs, all locations are not affected in the same way. For example, a fire in a plant may decrease production capacity but an earthquake in a demand zone may increase demand for first-aid products drastically, but decrease demand for luxury products. For this reason, depending on their nature, locations $l \in L$ are classified in *vulnerability source* subsets with similar impacts and time to recovery. Let S be the set of all relevant vulnerability sources. The notation $s(l)$ is used to denote the vulnerability source $s \in S$ characterizing location $l \in L$. In a SCN, transportation means are also used to move materials between locations. The potential locations and moves considered when designing a supply chain define a network similar to the one illustrated on the vulnerability source layer of **Figure 6**.

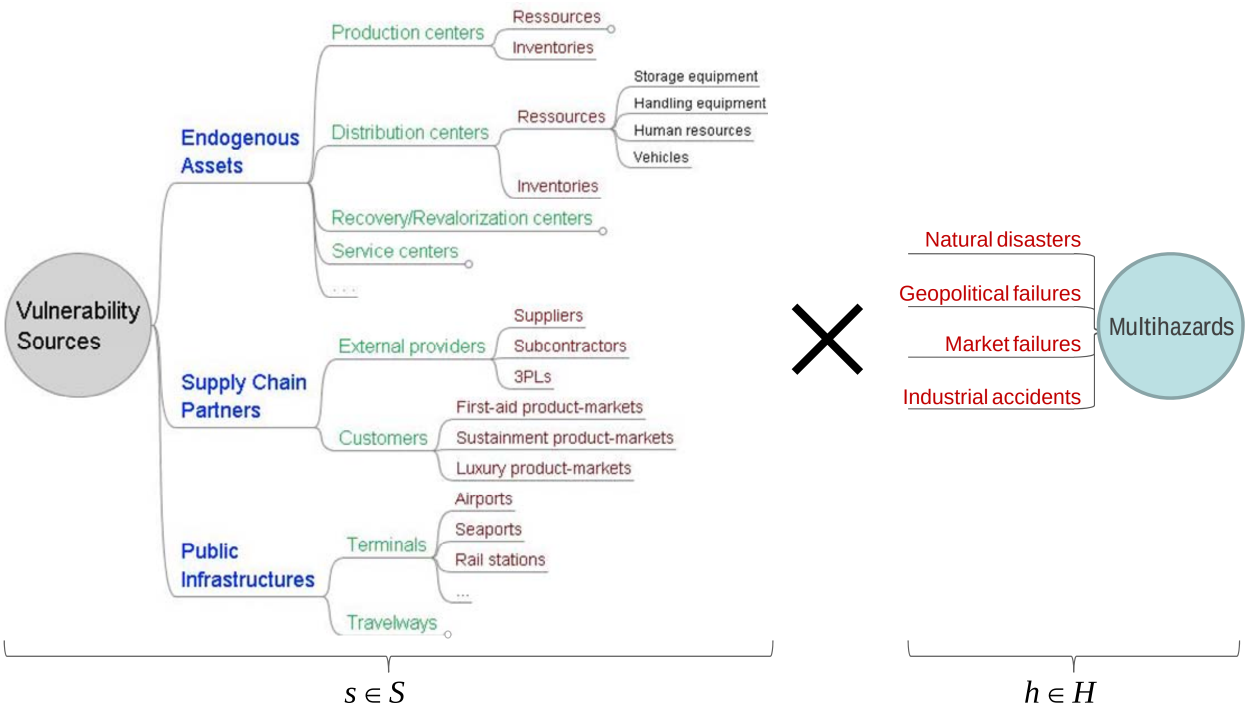

Figure 5. Examples of Vulnerability Sources and Multihazards

When considering potential risks arising from natural, accidental and wilful hazards on the SCN, a large set of vulnerability sources can be identified (Helferich and Cook, 2002). 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 included in the set *S*. The vulnerability sources 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 that all strategic vulnerabilities come from the SCN locations $l \in L$ and not from 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. This may lead to the definition of more than one location *l* for a same geographical region. For example, if the sales of two product categories in the same region (say first-aid products and luxury products) are not affected in the same way by a multihazard (one may increase and the other decrease), then they must be distinguished by associating them to different locations. Similarly, in a military context, potential humanitarian relief missions and peace-keeping missions in a same geographical area must be distinguished because they do not require the same material.

Natural, accidental and wilful hazards cover large classes of incidents which do not necessarily affect SCN vulnerability sources in the same way. Also, depending on the scope of the study, some hazard types may not be relevant. For example, when designing an American network, natural disasters are relevant, but the risk of armed conflicts resulting from a political failure is negligible. However, when designing an international SCN, potential state failures must be taken into account. Finally, even if a hazard type is relevant, for some parts of the world the data required to characterize it may not be available. For all these reasons, for a given SCN design study, a set *H* of multihazards to consider must be specified. Such a multihazard set is illustrated in **Figure 5**. 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). Vulnerability source threat domains must also be defined by specifying the subset $H_s \subseteq H$ of multihazards which have an impact on each vulnerability source $s \in S$.

In what follows, we assume that extreme event threats are not directly related to the resources/partners involved in the SCN but rather to the vulnerability source they are associated to and to their geographical location. In order to map threats, 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, as illustrated in **Figure 6**. Hazard zones delineate areas with similar geological, meteorological, political, economical and critical infrastructure characteristics. These zones may correspond to counties, to states/provinces, to countries, to 3-digit zip-codes, 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 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. The zonation process is a key issue since the zone granularity determines the realism of the multihazard incidents considered in the SCN optimization model.

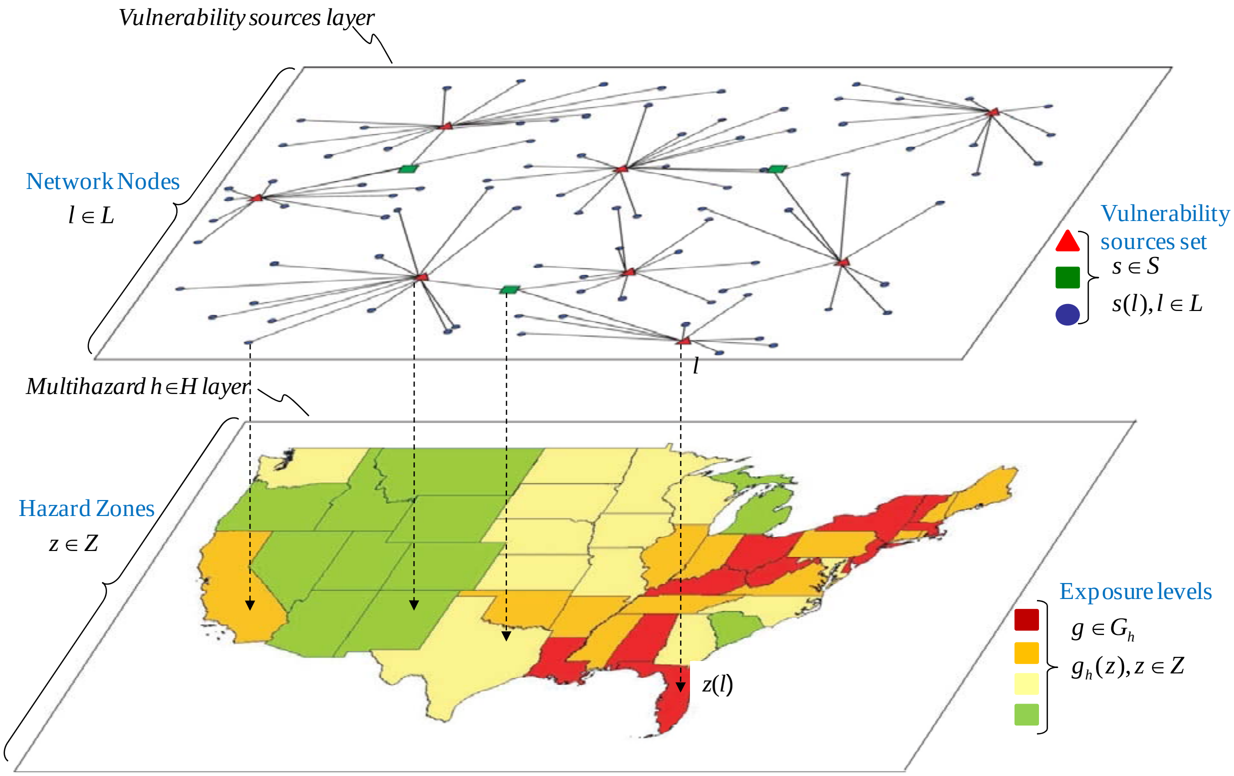

Figure 6. SCN Exposure Modeling

Unfortunately, with the data available, it is often difficult to estimate hazard arrival and impact processes directly at the hazard zone level. For each multihazard $h \in H$, this leads to the introduction of a set G_h of zone aggregates called *exposure levels*. The notation $g_h(z)$ is used to denote the exposure level $g \in G_h$ including hazard zone $z \in Z$, and $Z_g \subset Z$ the set of zones in exposure level $g \in G_h$. 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 the 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. For a multihazard $h \in H$, this defines an exposure map such as the one illustrated on the multihazard exposure layer in **Figure 6**. 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. The exposure level $g_h(l) = g_h(z(l))$ of a location $l \in L$ can be uniquely determined for each multihazard $h \in H$. This initial analysis phase thus leads to the specification of multihazard classes $(s,g) \in S \times G_h,\ h \in H$, with associated mutually exclusive and collectively exhaustive location subsets $L_{sg}^h = \{ l \mid s(l) = s, g_h(l) = g \}$.

Modeling of multihazard processes

The SCN designed must cope with the future and thus the modeling of future extreme events must take possible evolutionary paths into account. 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. More specifically, 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 $\phi_k^h(\mu_{z\delta_1}^h, \tau)$ be a function elaborated by experts to superimpose a time pattern for evolutionary path k on $\mu_{z\delta_1}^h$, the historical mean time between multihazards $h \in H$ in hazard zone $z \in Z$ estimated at the beginning of the planning horizon (i.e. at time δ_1). Then, the required probability distributions are obtained simply by calculating $\mu_{zk\tau}^h = \phi_k^h(\mu_{z\delta_1}^h, \tau)$ for all *h*, *z*, *k* and τ.

When designing a domestic SCN in America, the data required to estimate arrival processes directly at the hazard zone level can be obtained relatively easily. However, when designing a global SCN, the data provided by organizations such as CRED and HIIK is not sufficiently detailed to support such an approach. A hierarchical modeling approach based on exposure level arrival processes and conditional hazard zone hit probabilities must then be used. Let $\lambda_{gk\tau}^h$ be a random variable, with cumulative distribution function $F_{gk\tau}^{\lambda^h}(.)$, representing the time before the arrival of the next multihazard $h \in H$ in exposure level (region) $g \in G_h$ under evolutionary path $k \in K$ when an incident occurs in working period $\tau \in T^u$. Also, proceeding as in the previous paragraph, let $\mu_{gk\tau}^h = \phi_k^h(\mu_{g\delta_1}^h, \tau)$ be the mean time between multihazards $h \in H$ in exposure region $g \in G_h$ under evolutionary path *k* when in working period τ. This process models the arrival of incidents in the exposure regions, but it does not specify in which hazard zone within the region the multihazard occurs. In order to specify this zone, subjective conditional hit probabilities can be estimated from public or constructed indexes $I_z^h,\ z \in Z,\ h \in H$. For example, for geopolitical failures the *Failed State Index* published yearly by *Foreign Policy* (www.foreignpolicy.com) can be used, and for natural disasters an incident occurrence frequency calculated from CRED data can be used. Using such indexes, for a given multihazard $h \in H$ and exposure region $g \in G_h$, the following conditional probability mass function can be calculated: $p^h_{z|g} = I^h_z \Big/ \sum_{z \in Z_g} I^h_z$, $z \in Z_g$.

Intuitively, it appears that the impact intensity and duration of hazards are usually highly correlated. We thus 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^h_g, with cumulative distribution function $F^{\beta^h}_g(.)$ and the duration θ^h_g. The duration is related to the intensity through *incident impact-duration functions* $\theta^h_g = f^h\left(\beta^h_g\right) + \varepsilon^h$, $h \in H$, estimated by regression, and with a random error term $\varepsilon^h \sim \text{Normal}(0, \sigma^h_\varepsilon)$. These distribution functions and incident impact-duration functions can be estimated from the data provided by organizations such as CRED, HIIK, FEMA and USGS.

Modeling the impact of hits on the SCN

The occurrence of an extreme event in hazard zone *z* does not necessarily imply that all the SCN locations $l \in L_z$ will be hit. 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. When designing a pre-positioning supply network for a humanitarian or military organization, for example, the organization's response to a natural disaster may depend on its policies, on UN solicitations and on other commitments (Girard *et al*., 2008). In such cases, a demand surge for first-aid products in a hazard zone does not necessarily generate demands in the corresponding SCN demand zone. This leads to the estimation of *attenuation probabilities* α^h_l which are conditional probabilities that location 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 the SCN is hit, this has impacts on the network capacity and demand. In order to model these impacts, we need to refine our representation of the SCN. A hit on vulnerability sources such as plants, distribution centers (DCs) and suppliers result mainly in capacity loss, but a hit on product-markets affects demand processes. To reflect this, we partition the vulnerability source set *S* in two subsets: capacity-based sources S^{c} and demand-based sources S^{d}. Also, in SCN design projects, the products manufactured and sold are usually aggregated into a set of product families $p \in P$, and the subset of product families $P_s \subset P$ associated to each vulnerability source $s \in S$ needs to be identified. Finally, to model impacts, we need to define a parameter c_{lp} denoting the capacity of location $l \in L_s$, $s \in S^{c}$, for product $p \in P_s$, and a random variable $d_{lp\tau}$, with cumulative distribution function $F^{d}_{lpk\tau}(.)$, specifying the normal operations demand of location $l \in L_s$, $s \in S^{d}$, for product $p \in P_s$ in period $\tau \in T^{u}$, under evolutionary path $k \in K$.

When a location $l \in L$ in zone $z(l)$ is hit by a multihazard $h \in H$, the severity of the incident is characterized on two correlated dimensions: the impact intensity and the time to recovery (Sheffi, 2005). Clearly, these dimensions are related to the generic multihazard intensity and duration variables β^{h}_{g} and θ^{h}_{g} 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 such as the ones illustrated in **Figure 7** 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. In some cases, an engineering analysis may be required to establish the fragility of vulnerability source resources depending on the building type, age, etc.

			Capacity-based Vulnerability Sources $S^{c} = \{1, 2, 3\}$			Demand-based Vulnerability Sources $S^{d} = \{4, 5, 6\}$		
			1) **Suppliers**	2) **Plants**	3) **DCs**	4) **First-aid Product-markets**	5) **Sustainment Product-markets**	6) **Luxury Product-markets**
Impact intensity	**Multihazards** $H = \{a, b, c\}$	*a) Natural disasters*	Unfilled supply rate	Capacity loss rate	Capacity loss rate	Demand inflation rate		Demand deflation rate
		b) Market failures	Unfilled supply rate				Demand deflation rate	Demand deflation rate
		c) Industrial accidents		Capacity loss rate				
Time to recovery	**Multihazards** $H = \{a, b, c\}$	*a) Natural disasters*	Time to restoring supplies	Time to restarting production	Time to restarting distribution	Surge duration		Drop duration
		b) Market failures	Time to restoring supplies				Drop duration	Drop duration
		c) Industrial accidents		Time to restarting production				

Severity dimensions metrics

Figure 7. Multihazard Incident Profiles Example

Let ξ^{h}_{l} 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 $\theta^{h}_{g(l)}$ using an adequate translation function $\xi^{h}_{l} = q^{h}_{s(l)}(\theta^{h}_{g(l)})$

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 multi-hazard $h \in H$ hitting location $l \in L$ at the beginning of working period $\tau' \in T^u$. Then, the impact of the hit lasts during working 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. On the other end, when a disaster relief organisation initiates an assistance mission, it typically involves the three following phases: deployment, sustainment and redeployment. Such phase-dependent impacts can be characterized by defining discrete recovery functions $\boldsymbol{\rho} = r_{sp}^h(\beta, \xi, \boldsymbol{\rho}),\, h \in H,\, s \in S,\, p \in P_s$, 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 multi-hazard. 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, as illustrated in **Figure 8**. If the working periods affected by the multihazard are not still recuperating from a previous incident, then the a priori percentages are ρ_τ=100%, $\tau = \tau',...,\tau' + \xi - 1$. The amplitude of the amplification percentages depends on β, the multihazard generic impact intensity measure. Multihazard recovery functions are defined by experts for each vulnerability source and product family, based on experience and data available.

Using these recovery functions, the capacity available or the demand can be calculated for specific working periods and locations. More specifically, the behaviour of the capacity $c'_{lp\tau}$ or the demand $d'_{lp\tau}$ resulting from a multihazard $h \in H$ is described by the following relations:

$$c'_{lp\tau} = \rho_{lp\tau} c_{lp},\ \ \tau = \tau',...,\tau' + \xi_l^h - 1;\ \boldsymbol{\rho}_{lp} = r_{sp}^h(\beta_{g(l)}^h, \xi_l^h, \boldsymbol{\rho}_{lp});\ \ s \in S^{\mathrm{c}}, p \in P_s,\ l \in L_s \qquad (1)$$

$$d'_{lp\tau} = \rho_{lp\tau} d_{lp\tau},\ \ \tau = \tau',...,\tau' + \xi_l^h - 1;\ \boldsymbol{\rho}_{lp} = r_{sp}^h(\beta_{g(l)}^h, \xi_l^h, \boldsymbol{\rho}_{lp});\ \ s \in S^{\mathrm{d}}, p \in P_s,\ l \in L_s \qquad (2)$$

This SCN impact modeling approach is based on a simplified representation of SCN resources, but it should be relatively easy to adapt to the specificities of real life cases. In particular, expressions (1) and (2) reflect multiplicative impacts, which is typically appropriate in business contexts. However, for humanitarian relief or military organizations, the demand is usually more adequately described using additive impact relationships because $d_{lp\tau}$ can be zero when there is no incident. Also, we assumed that multihazard recovery functions are not affected by evolutionary paths, which is not always the case.

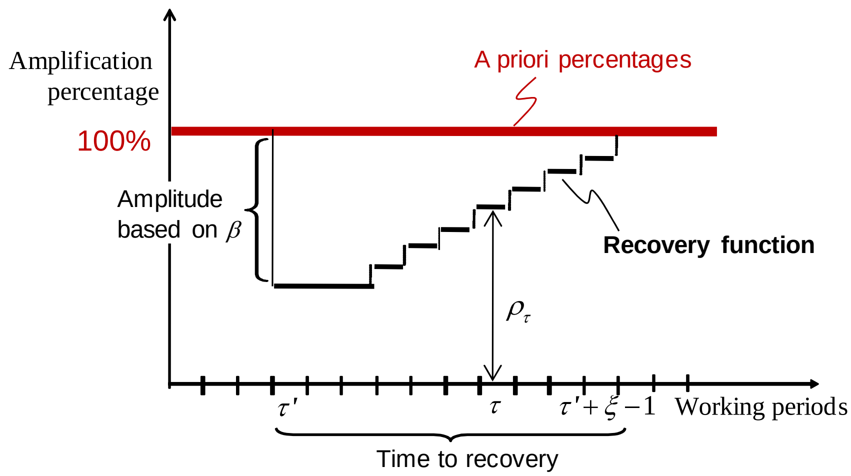

Figure 8. Recovery Function for a Given $h \in H$, $s \in S^c$ and $p \in P_s$

Plausible future scenarios

The SCN hazard modeling framework proposed in the previous paragraphs is based on a number of key concepts: the identification of evolutionary paths *K*, the classification of SCN locations L into vulnerability sources *S* and of hazards into multihazards *H*, the zonation of the territory into hazard zones *Z* and their classification into exposure levels *G*, the definition of incident profiles in terms of impact intensity and time to recovery with associated recovery functions, and the characterization of multihazards likelihood through the use of incident arrival stochastic processes, impact intensity probability distribution functions, incident impact-duration functions and attenuation probabilities. The superposition, during the planning horizon, of a specific instance of this hazard occurrence process over specific instances of the business-as-usual random variables used to model the SCN yield a probabilistic scenario $\omega \in \Omega^P$. 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 $\gamma(\omega)$ it undergoes during the planning horizon. **Figure 9** 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 the decision maker can tolerate without serious concern. This tolerance level is used to partition the set of probabilistic scenario Ω^P in two subsets, namely Ω^A the set of acceptable-risk scenarios and Ω^S the set of serious-risk scenarios.

For a given SCN design project, the sets, measures and functions required to characterize hazards are necessarily defined based on the information and experience available and, consequently, they 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 must be elaborated. Some uncertain extreme events associated with these scenarios can be identified through structured brainstorming sessions and/or expert interviews related to SCN threats and vulnerabilities (Van der Heijden, 2005). However, for our purposes, the resulting scenarios must be expressed quantitatively in terms of the parameters used in the design model. This can be achieved by following the structured process described in this section but by replacing probability distributions and impact functions by human inputs for multihazards which cannot be described probabilistically. Also, these scenarios necessarily include random events and they may also include probabilistic hazards so they are most easily created by perturbating probabilistic scenarios. In what follows, our interest in deep uncertainty scenarios will be mainly related to our need to generate worst case scenarios. These would typically be probabilistic scenarios in the tail of the distribution of the number of hits, as illustrated in **Figure 9**, or serious-risk scenarios perturbated by deep-uncertainty events imagined by experts. Our challenge now is to elaborate a SCN design modeling framework taking all this into account.

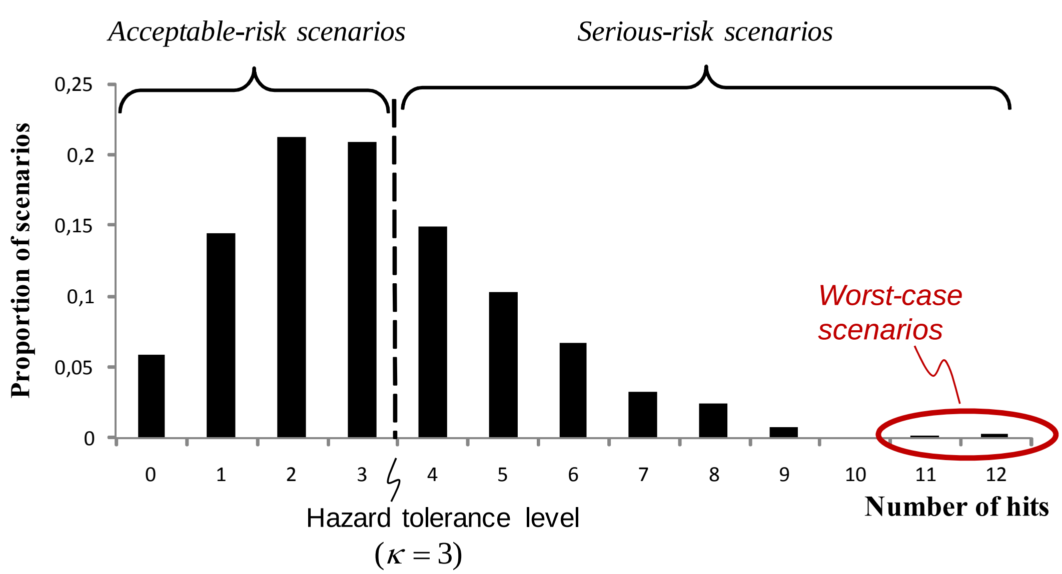

Figure 9. Distribution of the Number of Hits for a Large Sample of Scenarios

SCN Design Model

The generic design model proposed in **Figure 2** does not take the nuances introduced in the previous section into account explicitly. More specifically, in **Figure 2**, the generalized future return measure $\mathbf{R}\{.|I^{\Omega}(\delta_1)\}$ used is defined over the set of all scenarios Ω and it does not take the partitioning into acceptable-risk, serious-risk, and deeply uncertain scenarios into account. A fundamental argument of risk analysis is that this should not be done because it gives the same weight to normal impact and serious impact events. To avoid this pitfall, in risk analysis, traditional expected value assessment functions are replaced by a set of conditional expected value assessment functions taking the impact of various types of events into account (Haimes, 2004). Along this line of thinking, in our SCN design methodology, to take into account the quality of information available and the impact intensity of events (as described in **Figure 3**), we propose to replace our original future return measure by three conditional return functions defined over the scenario subsets Ω^A, Ω^S and Ω^U respectively.

This transforms our original model into the following multiobjective program:

$$\max_{\mathbf{x}_1 \in \mathbf{X}_1} \left\{ \mathbf{R}_{\Omega^A|A} \left\{ C\left(\mathbf{x}_1,.\right) \right\}, \mathbf{R}_{\Omega^S|S} \left\{ C\left(\mathbf{x}_1,.\right) \right\}, \mathbf{R}_{\Omega^U|U} \left\{ C\left(\mathbf{x}_1,.\right) \right\} \right\} \tag{3}$$

$$\mathbf{R}_{\Omega^A|A} \left\{ C\left(\mathbf{x}_1,.\right) \right\} = \mathbf{E}_{\Omega^A|A} \left\{ C\left(\mathbf{x}_1,.\right) \right\} + \varphi_A \mathbf{D}_{\Omega^A|A} \left\{ C\left(\mathbf{x}_1,.\right) \right\}, \varphi_A \in [0,1] \tag{4}$$

$$\mathbf{R}_{\Omega^S|S} \left\{ C\left(\mathbf{x}_1,.\right) \right\} = \mathbf{E}_{\Omega^S|S} \left\{ C\left(\mathbf{x}_1,.\right) \right\} + \varphi_S \mathbf{D}_{\Omega^S|S} \left\{ C\left(\mathbf{x}_1,.\right) \right\}, \varphi_S \in [0,1] \tag{5}$$

$$\mathbf{R}_{\Omega^U|U} \left\{ C\left(\mathbf{x}_1,.\right) \right\} = \underset{\omega \in \Omega^U}{Min}\ \mathbf{D}_U \left\{ C\left(\mathbf{x}_1,\omega\right) \right\} \tag{6}$$

where $\mathbf{R}_{\Omega^A|A}(C)$, $\mathbf{R}_{\Omega^S|S}(C)$ and $\mathbf{R}_{\Omega^U|U}(C)$ are conditional return functions for scenarios in Ω^A, Ω^S and Ω^U, respectively, defined in terms of the conditional expected value $\mathbf{E}_{\Omega^A|A}(C)$ and $\mathbf{E}_{\Omega^S|S}(C)$ of random variable *C*, of the conditional measures of dispersion (variability) $\mathbf{D}_{\Omega^A|A}(C)$ and $\mathbf{D}_{\Omega^S|S}(C)$ of random variable *C* and of the weights φ_A and φ_H. When $\mathbf{D}_{\Omega^A|A}(C)$ and $\mathbf{D}_{\Omega^S|S}(C)$ are *coherent risk measures*, $\mathbf{R}_{\Omega^A|A}(C)$ and $\mathbf{R}_{\Omega^S|S}(C)$ are also coherent risk measures (Rockafellar, 2007). Coherent risk measures must satisfy a number of convexity, monotonicity, translation equivalence and positive homogeneity conditions. The most convenient coherent dispersion measures to use in our context are

$$\mathbf{D}\{C\} = \mathbf{E}\{[\mathbf{E}(C) - C]_+\} \quad \text{or} \quad \mathbf{D}\{C\} = \min_{r \in \mathbf{R}} \mathbf{E}\{[C - r]_+ + \nu[r - C]_+\}, \ \nu \geq 0$$

where $[c]_+ = \max(c, 0)$ and ν is a constant. The former is a mean-semideviation risk function and the later the so-called conditional value at risk function (Shapiro, 2007).

Since the probability of occurrence of scenario $\omega \in \Omega^U$ is not known, expected value and dispersion measures cannot be defined for *U*-scenarios. For this reason, for *U*-scenarios, we use conditional return functions $\mathbf{R}_{\Omega^U|U}(C)$ based on the robust optimization criteria proposed by Kouvelis and Yu (1997). In our context, it is most convenient to use the *absolute robustness* or *robust deviation* criteria defined respectively by:

$$\mathbf{D}_U \left\{ C\left(\mathbf{x}_1,\omega\right) \right\} = -C\left(\mathbf{x}_1,\omega\right) \quad \text{or} \quad \mathbf{D}_U \left\{ C\left(\mathbf{x}_1,\omega\right) \right\} = \left[C\left(\mathbf{x}_1^{\omega},\omega\right) - C\left(\mathbf{x}_1,\omega\right) \right]$$

where $\mathbf{x}_1^{\omega}$ is the optimal single scenario design obtained when scenario ω is realized, i.e. where $\mathbf{x}_1^{\omega} = \arg\{\max_{\mathbf{x}_1 \in \mathbf{X}_1} C(\mathbf{x}_1,\omega)\}$. From a computational point of view, the absolute robustness criterion is more attractive because it does not require the optimal decision for each scenario but, according to Kouvelis and Yu (1997), it leads to very conservative decisions. The robust deviation criterion is more adequate in our context but it requires more computations.

Several methods are proposed in the literature to solve multiobjective programming problems. Given the complexity and size of model (3), an adequate approach here is to simply convert it into the multiparametric program:

$$\max_{\mathbf{x}_1 \in \mathbf{X}_1} R(\mathbf{x}_1) = (1-\psi)\left[w_A \mathbf{R}_{\Omega^A|A}\left\{C\left(\mathbf{x}_1,.\right)\right\} + w_S \mathbf{R}_{\Omega^S|S}\left\{C\left(\mathbf{x}_1,.\right)\right\}\right] + \psi \mathbf{R}_{\Omega^U|U}\left\{C\left(\mathbf{x}_1,.\right)\right\} \qquad (7)$$

with subjective weights $0 \le w_A \le 1,\ w_S = 1 - w_A, 0 \le \psi \le 1$. Since $R(\mathbf{x}_1)$ is a convex combination of coherent risk measures, it is also a coherent risk measure (Rockafellar, 2007). Such an approach leads to satisfactory designs only if program (7) is solved parametrically for different weight values. Note that when the probabilities $p(\omega)$ for all probabilistic scenarios can be evaluated, and when the decision maker is neutral to risk, we have $\varphi_A = \varphi_S = 0$ in (4) and (5), and $\psi = 0$. Under these conditions, by defining the weight $w_A = \pi_A = \Sigma_{\omega \in \Omega^A} p(\omega)$, the probability of acceptable-risk scenarios, and $w_S = \pi_S = 1 - \pi_A$, the probability of serious-risk scenarios, (7) reduces to the maximization of the unconditional expected value of $C\left(\mathbf{x}_1,.\right)$. On the other end, a decision maker averse to extreme events would define weights $w_A < \pi_A$ and $\psi > 0$, and a decision-maker averse to dispersion would set $\varphi_A > 0$ and $\varphi_S > 0$. Note however that, in most practical cases, the number of possible scenarios $|\Omega|$ is extremely large, if not infinite, and thus it is impossible to obtain the set Ω^P and the probabilities $p(\omega), \omega \in \Omega^P$ explicitly.

Our previous discussion of extreme events has another impact on the formulation of SCN design models. When facing such threats, one would like to design the SCN to avoid risky locations as much as possible and to be able to bounce back quickly when hit, i.e. to favour network structures and response policies helping the user to react efficiently when hit. This is the domain of resilience strategies (Sheffi, 2005). Clearly, resilient designs improve the SCN robustness. In order to obtain resilient designs, additional decision variables and constraints may have to be included in the formulation of the solution sets $\mathbf{X}_1, \hat{\mathbf{X}}_n^{\mathbf{x}_{n-1}}\left(\omega\right), n \in N \backslash \{1\}$. For example, one may want to provide instructions on the backup depot to use to supply customers when the primary depot is hit, or to impose primary and backup distance covers to ensure an adequate response to all customers (Klibi and Martel, 2009). Unfortunately, this further complicates the design model. Note finally that the anticipated adaptation-response model in **Figure 2** must incorporate an evaluation of the recourses necessary to obtain a feasible solution under any scenario $\omega \in \Omega$. All this certainly lead to extremely complex optimization models under uncertainty. In what follows, we propose a generic SCN design approach based on reasonable approximations of model (7).

Scenario-based SCN Design Model Solution Approach

SCN design model (3) is a multi-stage stochastic program with an infinite set of scenarios, a multiobjective reward function, and an anticipation of adaptation-response decisions. Unfortunately, this model is intractable in its current form, and the objective of this section is to propose a complexity reduction approach to obtain solvable SCN design models capturing the essence of the problem. Our purpose is not so much to obtain the optimal design as it is to identify practical ways of hedging risks that are largely overlooked in classical SCN models. The approach is based on several accuracy-solvability tradeoffs likely to yield effective and robust SCN designs.

A first complexity reduction avenue is to use approximate anticipations of adaptation-response decisions to simplify the combinatorial structure of the design model. A second simplification is to reduce the multiobjective function to a multiparametric function based on (7), and capturing only the primordial expected value and risk aversion criteria associated to probabilistic scenarios. A third opportunity comes from the fact that SCN design problems are usually solved on a rolling horizon basis so that the only decisions implemented when the model is solved are the first design decisions $\mathbf{x}_1^*$. This suggests that the model can be reduced to a multi-cycle two-stage stochastic program with recourse without loosing its hedging capabilities, which simplifies both the generation of scenarios and the resolution of the model. Finally, the resulting stochastic program can be solved using several samples of scenarios generated using Monte Carlo methods. The approach then reduces to solving a set of large MIPs, as done when solving stochastic programs with the Sample Average Approximation (SAA) method (Shapiro, 2003). Additional designs can be obtained by varying the anticipation granularity and the objective function weights. The designs obtained are then compared using performance measures (4)-(7), evaluated with a more precise adaptation-response model than the one incorporated in the design model and a larger scenario sample.

The SCN design approach thus obtained is summarized in **Figure 10**. It includes three phases: scenario generation, design generation and design evaluation. The first phase involves the generation of several plausible future scenario samples for the design generation and evaluation phases. It produces I independent small Monte Carlo samples of m_A acceptable-risk scenarios and m_S serious-risk scenarios, $\Omega_i^m = \Omega_i^{m_A} \cup \Omega_i^{m_S}$, $i = 1,...,I$, as well as estimates $\bar{\pi}_A$ and $\bar{\pi}_S$ of the probabilities π_A and π_S, for the design generation phase. It also provides larger samples $\Omega^{M_A}, \Omega^{M_S}$ of probabilistic scenarios, and a sample Ω^{M_U} of worst-case scenarios to the design evaluation phase. The second phase of the approach involves the resolution of the MIPs SAA(Ω_i^m), $i = 1,...,I$, resulting from the approximations made. For a given resilience and response anticipation formulation, this yields a set of distinct designs $\mathbf{x}_1^j, j = 1,...,J$ ($J \le I$). The third phase of the approach compares the performance of these designs, and of the status quo design $\mathbf{x}_1^0$, by solving an approximate adaptation-response model for each of the scenarios in $\Omega^M = \Omega^{M_A} \cup \Omega^{M_S} \cup \Omega^{M_U} \cup \{\omega^0\}$, where ω^0 is an historical scenario. The set of scenario specific design values $\tilde{C}\left(\mathbf{x}_1^j,\omega\right)$, $\omega \in \Omega^M$, thus obtained are used to evaluate performance measures $\mathrm{R}_{\Omega^{M_A}|A}\{\tilde{C}(\mathbf{x}_1^j,.)\}$, $\mathrm{R}_{\Omega^{M_S}|S}\{\tilde{C}(\mathbf{x}_1^j,.)\}$, $\mathrm{R}_{\Omega^{M_U}|U}\{\tilde{C}(\mathbf{x}_1^j,.)\}$ and $R(\mathbf{x}_1^j)$ based on (4)-(7). Finally, classical multicriteria filtering and selection techniques can be used to select the design $\mathbf{x}_1^*$ to implement. In what follows each phase of this generic design approach is discussed and explained in more details.

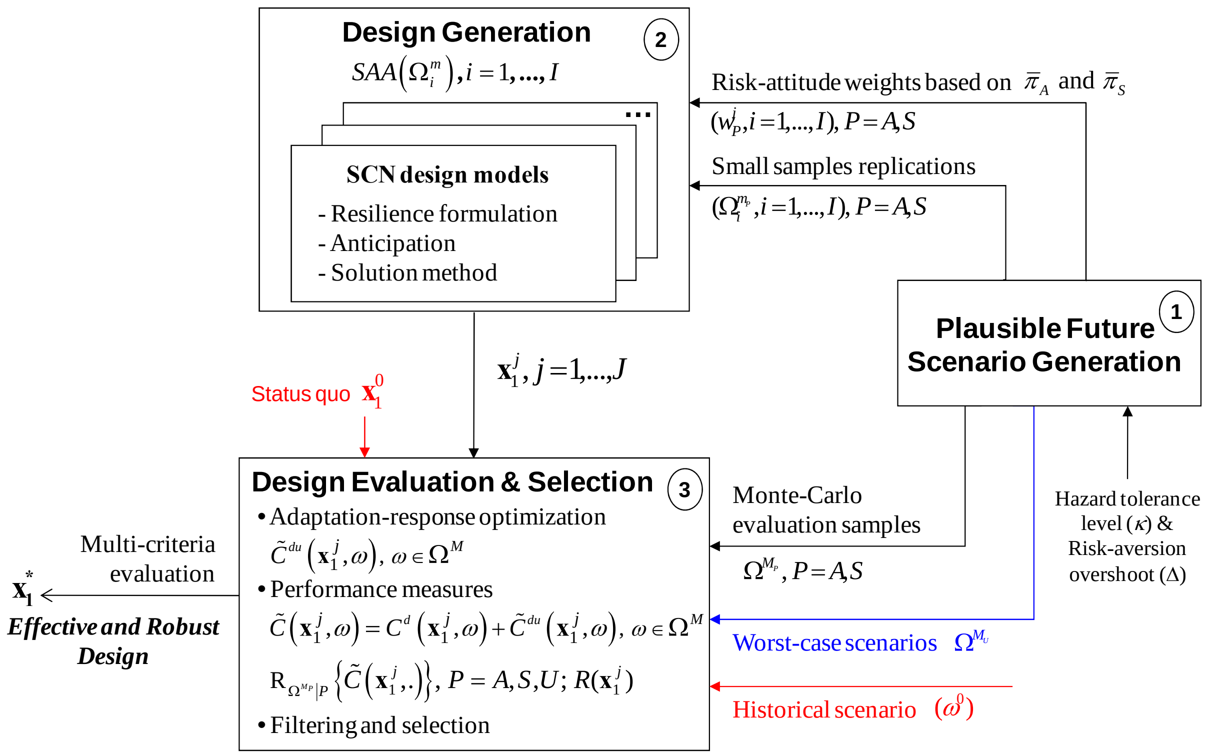

Figure 10. Generic SCN Design Methodology

SCN Designs Generation

As indicated previously, four complexity reduction stratagems can be used to formulate solvable SCN design models. The first one involves the incorporation of approximate anticipations of adaptation-response decisions in the design model. In classical SCN design models user decisions are anticipated using continuous throughput and flow variables. The anticipation variables are typically aggregates over several products, customers, transportation means and working periods. These decision variables are used to anticipate revenues and expenses, but they cannot be implemented. For example, in practice, flow decisions take the form of daily shipments in response to specific customer orders, and not the form of an annual quantity of products to ship between two locations. The later is used as a crude approximation of the former. In fact, such approximations are often so crude, that they raise issues about the validity of the model. Some authors have proposed models with more accurate anticipations: a model incorporating detailed market response anticipations is proposed by Vila *et al.*, (2007), and more elaborated transportation and inventory costs anticipations are proposed in the location-routing and location-inventory models reviewed in Shen (2007). Klibi *et al.*, (2009b) studied various anticipations for the stochastic location-transportation problem, based on different demand representations (multiple scenarios vs average demand) and on different aggregations of transportation decisions (route vs flows), customers (ship-to-point vs demand zones) and time (working periods vs planning periods). The results obtained show that although significant gains can be made by using more precise anticipations, given the computational power currently available, some tradeoffs are necessary. The best approach seems to be to seek an adequate equilibrium between all the dimensions involved instead of neglecting some dimensions (ex: using a deterministic model to be able to anticipate transportation costs with route-variables). The use of adequate approximate anticipations reduces the size of the multi-stage stochastic program to solve.

A second complexity reduction avenue is the replacement of the multiobjective function in model (3) by a simplified version of the composite return function (7), which is a convex combination of conditional return functions (4)-(6). The return functions (4) and (5) are defined in term of an expected value and a dispersion measure. Since the recourse variables included in the anticipation sub-model tend to be very expensive, the stochastic program tries to eliminate any extreme behaviour, which naturally reduces variability even if the dispersion terms are not included in these return functions. For this reason, a convenient complexity reduction mean is to set $\varphi_A = \varphi_S = 0$ in functions (4) and (5), respectively. Also, the aim of return function (7) is to reflect the consequences of extremely hazardous deeply uncertainty scenarios. However, since the probabilistic scenarios were separated into acceptable and serious risk scenarios, one can give more importance to extreme events if desired by increasing weight w_S. For this reason, another reasonable complexity reduction opportunity is simply to set $\psi = 0$. This reduces the original design model to the simpler multi-stage stochastic program:

$$\max_{\mathbf{x}_1 \in \mathbf{X}_1} \left[w_A \mathbf{E}_{\Omega^A|A} \left\{ C\left(\mathbf{x}_1, \boldsymbol{.}\right) \right\} + w_S \mathbf{E}_{\Omega^S|S} \left\{ C\left(\mathbf{x}_1, \boldsymbol{.}\right) \right\} \right] \tag{8}$$

Recall that, to take the risk attitude of decision makers into account, the weights w_A and w_S should be based on the probabilities π_A and π_S. These probabilities are not available but the weights can be based on the estimates $\bar{\pi}_A$ and $\bar{\pi}_S$ provided by the scenario generation procedure.

The dynamics of the multi-stage decision structure described in **Figure 1** and **Figure 2** is an important source of complexity. When several planning cycles are considered, first-stage design decisions $\mathbf{x}_1$ are made here and now, and the subsequent structural adaptation decisions

$\mathbf{x}_2,...,\mathbf{x}_n$ are *implementable policies* (Shapiro, 2007) elaborated to respect non-anticipativity conditions. When this is taken into account explicitly, the size of the problem tends to blow up. However, since design decisions are made on a rolling horizon basis, the structural adaptation decisions $\mathbf{x}_2,...,\mathbf{x}_n$ will in fact be revised before they are implemented. In our context, they are essentially anticipation variables. Under these conditions, a reasonable complexity reduction assumption is to consider that the decisions $\mathbf{x}_2,...,\mathbf{x}_n$ must be made at the beginning of the planning horizon. This eliminates non-anticipativity constraints and transforms the model into a multi-cycle two-stage stochastic program. In most practical cases, the number of possible scenarios $|\Omega|$ is extremely large and, in order to solve (8), one needs to limit the number of scenarios considered and to avoid the explicit use of the probabilities $p(\omega),\ \omega \in \Omega^P$. Another complexity reduction method is to replace the population sets Ω^P in design model (8) by representative Monte Carlo samples Ω^{m_A} and Ω^{m_S} of m_A equiprobable acceptable-risk scenarios and m_S equiprobable serious-risk scenarios, respectively. Clearly, the quality of the design obtained with the resulting SAA program depends on the number $m = m_A + m_S$ of scenarios considered. To get better designs, the model can be solved with I scenario sample replications $\Omega_i^m = \Omega_i^{m_A} \cup \Omega_i^{m_S}$, $i = 1,...,I$. Statistical gaps can be calculated to evaluate the quality of the solutions obtained with these scenario sets (Shapiro, 2003), and they can be used to calibrate the size of the scenario samples to generate. The SAA model to solve for a given scenario sample Ω_i^m is the following:

$$SAA(\Omega_i^m) \qquad \max \sum_{P=A,S} \frac{w_P^i}{m_P} \sum_{\omega \in \Omega_i^{m_P}} \left\{ C^d\left(\mathbf{x}_1, \omega\right) + \sum_{n>1} \hat{C}^d\left(\hat{\mathbf{x}}_n, \omega\right) + \sum_{t \in \hat{T}} \hat{C}^u\left(\hat{\mathbf{y}}_t\left(\omega\right)\right) \right\} \tag{9}$$

$$\text{s.t.} \quad \mathbf{x}_1 \in \mathbf{X}_1; \quad \hat{\mathbf{x}}_n \in \hat{\mathbf{X}}_n^{\mathbf{x}_{n-1}},\ n \in N \backslash \{1\} \tag{10}$$

$$\hat{\mathbf{y}}_t\left(\omega\right) \in \hat{\mathbf{Y}}_t^{\mathbf{x}_{n(t)}}\left(\omega\right),\ t \in \hat{T},\ \omega \in \Omega_i^m \tag{11}$$

Despite all the simplifications proposed, for real SCN design problems, program $SAA(\Omega_i^m)$ may still be extremely large and difficult to solve. Santoso *et al*. (2005) proposed the use of Benders decomposition to solve this type of SCN design models. Recent commercial solvers, such as CPLEX-11, incorporate generic heuristics (ex: the feasibility pump) to find good initial solutions and they are able to solve surprisingly large SCN design problems. Also, since our objective here is to generate good potential SCN 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 can be used to reduce computation times. Note finally that several heuristic methods were proposed in the literature to solve deterministic location-allocation problems (see Klibi *et al.* (2009a) for a review) and some of them can be extended relatively easily to solve stochastic versions of the problem.

By solving $SAA(\Omega_i^m), i=1,...,I$, a set of potentially effective and robust designs are obtained. However, the SAA program solved is based on a specific resilience and adaptation-response anticipation formulation, and on given risk-attitude weights. Other potential designs can be generated by modifying the model formulation or the risk-attitude weights. Modifying the model formulation may be cumbersome, but reformulations such as a change in the granularity of some anticipation variables are possible without excessive efforts. Changing risk-attitude weights is easy and, since these weights are not hard data, varying them is an adequate approach to generate alternative designs $\mathbf{x}_1^j, j=1,...,J$ ($J \le I$). One way to take into account the fuzzy nature of these weights, and to make sure that the designs obtained by solving the I SAA programs are all distinct, is to consider them as random variables with $w_S \sim \text{Uniform}\left[\bar{\pi}_S, \bar{\pi}_S + \Delta\right]$, $w_A = 1 - w_S$ and $\Delta < \bar{\pi}_A$. Since the overshoot parameter Δ determines the maximum value of w_S, its value is selected to reflects the risk-aversion of the decision-maker. The weights w_A^i and w_S^i used for model $SAA(\Omega_i^m)$ are generated randomly from this distribution.

Scenarios Generation

Plausible future scenario samples are required by the two other phases of the design methodology in **Figure 10**. As indicated before, scenarios are juxtapositions of random, hazardous and deeply uncertain events over the planning horizon $\hat{T}$, and they are shaped by possible evolutionary paths $k \in K$. When the decision process is approximated by a two-stage stochastic program, plausible futures can be represented as a fan of individual scenarios, as illustrated in **Figure 4**, and it is sufficient to generate particular event type realizations and to concatenate them to obtain a scenario. Importance sampling techniques (Ducapova *et al.*, 2000) can also be used to obtain scenario samples adequately covering all scenario types and evolutionary paths. In this section, we provide a procedure to generate individual scenarios and we discuss the generation of the various scenario samples required to obtain effective and robust SCN design.

As explained previously, random and hazardous events can be characterized by random variables with distribution functions depending on working periods $\tau \in T^u$ and on evolutionary paths $k \in K$. Also, some of the problem data may be considered as known but affected by hazards. To illustrate this, in the section on the modelling of hazards, we introduced a known constant capacity parameter c_{lp} and a time-dependent random demand variable $d_{lp\tau}$, both being subjected to the effects of hazards. To simplify the presentation we also assume in this section that capacity and demand are the only two variables affected by hazards. Other random variables related to prices, costs, exchange rates... may be influenced by evolutionary paths, but not by hazards. Let E be the set of all these random variables, denoted by $\zeta_\tau^e, e \in \mathrm{E}$, and let $F_{k\tau}^e(.), e \in \mathrm{E}$, be their cumulative distributions for working period $\tau \in T^u$ under evolutionary path $k \in K$. For a given scenario ω, the value taken by these variables is denoted by $c_{lp\tau}(\omega)$, $d_{lp\tau}(\omega)$ and $\zeta_{\tau}^{e}(\omega)$. The Monte Carlo procedure required to generate these values is given in **Figure 11**. In the procedure, u denotes a pseudorandom number, and $\Phi^{-1}(u)$ the inverse of the standardized Normal variate.

1) Select an evolutionary path k randomly using p_k, $k \in K$

2) For all $h \in H$ and $g \in G_h$, do:

    $\eta = 0$

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

        Compute the next multihazard arrival moment $\eta = \eta + F_{gk\tau}^{\lambda^h \; -1}(u)$

        Select a hazard zone z randomly in Z_g using $p_{z|g}^{h}$, $z \in Z_g$

        Insert the pair $(\lceil \eta \rceil, h)$ chronologically in the list T_z

    End While

End For

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

    Set $\rho_{lp\tau} = 1, l \in L, p \in P, \tau \in T^u$

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

        Compute $\beta_z^h = F_{g(z)}^{\beta^h \; -1}(u)$ and $\theta_z^h = f^h\left(\beta_z^h\right) + \sigma_h^{\varepsilon} \Phi^{-1}(u)$

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

            Compute $\xi_l^h = q_{s(l)}^h(\theta_{z(l)}^h)$

            Compute $\rho_{lp\tau} = r_{s(l)p}^h(\beta_{z(l)}^h, \xi_l^h, \rho_{lp\tau})$, $\tau = \tau', ..., \tau' + \xi_l^h - 1$, $p \in P_{s(l)}$

        End For

    End For

End For

4) For all $s \in S^c, l \in L_s, p \in P_s$ and $\tau \in T^u$: Compute the capacity $c_{lp\tau}(\omega) = \rho_{lp\tau} c_{lp}$

For all $s \in S^d, l \in L_s, p \in P_s$ and $\tau \in T^u$: Generate the demand $d_{lp\tau}(\omega) = \rho_{lp\tau} F_{lpk\tau}^{d \; -1}(u)$

For all $e \in \mathrm{E}$ and $\tau \in T^u$: Compute $\zeta_\tau^e(\omega) = F_{k\tau}^{e \; -1}(u)$

5) Aggregate these values over periods $\tau \in T_t^u$, $t \in \hat{T}$, to obtain $c_{lpt}(\omega)$, $d_{lpt}(\omega)$ and $\zeta_t^e(\omega)$

Figure 11. Monte Carlo Procedure for the Generation of a Scenario ω

The procedure includes five main steps. First, an evolutionary path is randomly selected. Then, a chronological list T_z of all the multihazards arrival periods is constructed for every hazard zone $z \in Z$. Third, the intensity and duration of the incidents are generated and used to calculate amplification factors using the recovery functions. Forth, the amplification factors are used to calculate the working period's capacity and demand. The value of the hazard-independent random variables is also computed. We assume here that the random variables ζ_τ^e, $e \in \mathrm{E}$, are independent. If they are not, the generation process is more complicated but straightforward. The last step aggregates the working period values obtained into planning period values. This is required because the design generation phase 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 $\tau \in T^u$. Note that this aggregation process does not always involve a simple sum over all the working periods $\tau \in T_t^u$, $t \in \hat{T}$. For the capacity, for example, in order to take congestion into account properly, this may involve period sampling or the application of a correcting factor.

The procedure in **Figure 11** can be used to generate all the scenarios, probabilities and risk-attitude weights required by the design generation phase. To do this, a large sample of M^d scenarios Ω^{M^d} is generated and partitioned into acceptable and serious hazard subsets $\Omega^{M_A^d}$ and $\Omega^{M_S^d}$, using the hazard tolerance level κ (see **Figure 9**). From these sub-samples, the probability estimates $\bar{\pi}_A = M_A^d / M^d$ and $\bar{\pi}_S = 1 - \bar{\pi}_A$ are calculated. The small scenario samples $\Omega_i^{m_A}$, $\Omega_i^{m_S}$, $i = 1,...,I$, are then randomly selected in $\Omega^{M_A^d}$ and $\Omega^{M_S^d}$, respectively. Through this hierarchical sampling procedure, one makes sure that all the scenarios in $\Omega_i^{m_A}$ and $\Omega_i^{m_S}$ are equiprobable, with probability $1/m_A$ and $1/m_S$ respectively. Based on $\bar{\pi}_S$ and on the risk-aversion overshoot factor Δ, the weights w_A^i, w_S^i, $i = 1,...,I$, can also be generated from the $\text{Uniform}\left[\bar{\pi}_S, \bar{\pi}_S + \Delta\right]$ distribution. Note that the samples obtained include scenarios coming from all the evolutionary paths $k \in K$. If m_A and m_S are relatively large, then each evolutionary path is well represented in the samples. However, if the sample size is small, one may want to force a good representation of each evolutionary path by hierarchically sampling m_{kA} scenarios for path *k* to get the samples $\Omega_i^{m_{kA}}$, $\Omega_i^{m_{kS}}$, $k \in K$, $i = 1,...,I$. The objective function (9) must then be replaced by:

$$\max \sum_{P=A,S} w_P^i \sum_{k \in K} \frac{p_k}{m_{kP}} \sum_{\omega \in \Omega_i^{m_{kP}}} \left\{ C^d\left(\mathbf{x}_1, \omega\right) + \sum_{n>1} \hat{C}^d\left(\hat{\mathbf{x}}_n, \omega\right) + \sum_{t \in \hat{T}} \hat{C}^u\left(\hat{\mathbf{y}}_t\left(\omega\right)\right) \right\} \tag{12}$$

The procedure in **Figure 11** can also be used to generate all the scenarios required by the design evaluation phase. To this end, another large sample of scenarios Ω^{M^e} is independently generated and partitioned into acceptable-hazard scenarios $\Omega^{M_A^e}$ and serious-hazard scenarios $\Omega^{M_S^e}$, 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 $\Omega^{M_A} \subset \Omega^{M_A^e}$ of M_A acceptable-hazard scenarios, and a subset $\Omega^{M_S} \subset \Omega^{M_S^e}$ of M_S serious-hazard scenarios. In order to obtain worst-case scenarios, a subset $\Omega^{M_W} \subset \Omega^{M_S^e}$ of tail scenarios is also selected in the distribution of the number of hits (see **Figure 9**). These scenarios are then taken as is, or modified manually by adding imaginative elements, to get the required set of worst-case scenarios Ω^{M_U}.

SCN Designs Evaluation

The aim of the design evaluation phase is to select the best SCN design among those generated ($\mathbf{x}_1^j, j=1,...,J$) and to compare them to the status quo $\mathbf{x}_1^0$. If we were applying the standard SAA approach, this would be done by solving the second stage program, obtained by fixing $\mathbf{x}_1^j$ and $\hat{\mathbf{x}}_n^j, n \in N\backslash\{1\}$, in (9)-(11), with the scenarios $\Omega^{M_A} \cup \Omega^{M_S}$, and then by comparing the designs expected value. 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 model as close as possible to the real user model. Moreover, to obtain the $SAA(\Omega_i^m)$ model, we assumed that the design adaptation decisions needed to be made at the beginning of the planning horizon. However, these decisions can be reoptimized to improve the assessment process. Finally, to obtain $SAA(\Omega_i^m)$, we simplified the objective function, but when comparing the designs, there is no reason not to use the performance evaluation measures (4)-(7).

Consequently, for a given design $\mathbf{x}_1^j$ and a given scenario $\omega \in \Omega^M$ (recall that $\Omega^M = \Omega^{M_A} \cup \Omega^{M_S} \cup \Omega^{M_U} \cup \{\omega^0\}$) the mathematical program to solve to obtain the net revenues provided by the design under this scenario is the following:

$$\tilde{C}^{du}\left(\mathbf{x}_1^j,\omega\right) = \max_{\substack{\hat{\mathbf{x}}_2,\hat{\mathbf{x}}_3 \dots \\ \tilde{\mathbf{y}}_1,\tilde{\mathbf{y}}_2 \dots}} \sum_{n>1} \hat{C}^d\left(\hat{\mathbf{x}}_n,\omega\right) + \sum_{\tau' \in T^u} \tilde{C}^u\left(\tilde{\mathbf{y}}_{\tau'},\omega\right) \tag{13}$$

$$\text{s.t.} \quad \hat{\mathbf{x}}_n \in \hat{\mathbf{X}}_n^{\mathbf{x}_{n-1}}, \; n \in N\backslash\{1\} \tag{14}$$

$$\tilde{\mathbf{y}}_{\tau'} \in \tilde{\mathbf{Y}}_{\tau'}^{\mathbf{x}_{n(\tau)}}\left(\omega\right), \; \tau' \in T^u \tag{15}$$

In this model, the response variables $\tilde{\mathbf{y}}_{\tau'}$, sets $\tilde{\mathbf{Y}}_{\tau'}^{\mathbf{x}_{n(\tau)}}\left(\omega\right)$ and functions $\tilde{C}^u\left(\tilde{\mathbf{y}}_{\tau'},\omega\right)$ are accentuated with a '~' instead of a ' ^ ' to reflect the fact that the user response can be anticipated more precisely than in the design model, even if an exact anticipation is usually not possible. Also, the index τ' instead of *t* is used to indicate that the time unit used can be a compromise between the working period τ and the planning period *t*. For example, one could use months or seasons as in tactical planning models. Since this model is solved for a single scenario at the time, it is much easier to solve than $SAA(\Omega_i^m)$. Note finally that $\tilde{C}^{du}\left(\mathbf{x}_1^j,\omega\right)$ does not include the investment costs associated to design $\mathbf{x}_1^j$. The design values for the sample of evaluation scenarios are thus provided by:

$$\tilde{C}\left(\mathbf{x}_1^j,\omega\right) = \tilde{C}^d\left(\mathbf{x}_1^j,\omega\right) + \tilde{C}^{du}\left(\mathbf{x}_1^j,\omega\right), \; \omega \in \Omega^M \tag{16}$$

These design values can be used to evaluate performance measures based on (4)-(7). Given the evaluation scenario samples generated, this yield the following measures:

$$\mathbf{R}_{\Omega^{M_A}|A}\left\{\tilde{C}\left(\mathbf{x}_1^j,.\right)\right\} = \mathbf{E}_{\Omega^{M_A}|A}\left\{\tilde{C}\left(\mathbf{x}_1^j,.\right)\right\} + \varphi_A \mathbf{D}_{\Omega^{M_A}|A}\left\{\tilde{C}\left(\mathbf{x}_1^j,.\right)\right\} \tag{17}$$

$$\mathbf{R}_{\Omega^{M_S}|S}\left\{\tilde{C}\left(\mathbf{x}_1^j,.\right)\right\} = \mathbf{E}_{\Omega^{M_S}|S}\left\{\tilde{C}\left(\mathbf{x}_1^j,.\right)\right\} + \varphi_S \mathbf{D}_{\Omega^{M_S}|S}\left\{\tilde{C}\left(\mathbf{x}_1^j,.\right)\right\} \quad (18)$$

$$\mathbf{R}_{\Omega^{M_U}|U}\left\{\tilde{C}\left(\mathbf{x}_1^j,.\right)\right\} = \underset{\omega\in\Omega^{M_U}}{Min}\ \mathbf{D}_U\left\{\tilde{C}\left(\mathbf{x}_1^j,\omega\right)\right\} \quad (19)$$

$$R(\mathbf{x}_1^j) = (1-\psi)\left[w_A \mathbf{R}_{\Omega^{M_A}|A}\left\{\tilde{C}\left(\mathbf{x}_1^j,.\right)\right\} + w_S \mathbf{R}_{\Omega^{M_S}|S}\left\{\tilde{C}\left(\mathbf{x}_1^j,.\right)\right\}\right] + \psi \mathbf{R}_{\Omega^{M_U}|U}\left\{\tilde{C}\left(\mathbf{x}_1^j,.\right)\right\} \quad (20)$$

We are left with a classical multicriteria decision making problem to determine the most effective and robust design $\mathbf{x}_1^*$. Formal multicriteria decision making techniques (Triantaphyllou, 2000) can be used to reach a decision, but simpler filtering and pegging methods can also help to examine the designs from different points of view. Filtering techniques can be used to eliminate dominated designs. Pegging can be performed to compare specific solutions with the status quo $\mathbf{x}_1^0$ for specific scenarios. In practice, managers particularly like to make such comparisons for the historical scenario ω^0 and for worst case scenarios $\omega \in \Omega^{M_U}$. Sensitivity analysis can be performed for the various risk-attitude weights φ_A, φ_S, w_A, w_S and ψ. In other words, several multicriteria/multi-scenario views can be elaborated to help select the best design.

Conclusions

This paper proposes a new methodology to design effective and robust SCNs. It underlines the temporal hierarchy between design time and utilization time, and it proposes to evaluate robustness through a high-quality anticipation of user decisions for a sample of adequately selected plausible future scenarios. In order to design superior SCNs, it is not sufficient to maximize overall effectiveness under normal operations, as is usually done in the literature: robustness under unpredictable disruptions must also be considered. An approach is proposed to take such disruptions into account in the design process. In addition to considering expected values, the approach considers the risk attitude of the decision maker. However, incorporating all these elements in the SCN design model yields an intractable multi-stage stochastic program. Given that, an approximate design methodology is proposed to capture the essence of the problem while preserving solvability. Complementary work performed to test the approach (Klibi *et al.*, 2009b; Klibi and Martel, 2009) indicates that it offers a judicious accuracy-solvability trade-off. We also believe that our framework provide ample opportunities for additional research.

References

[1] Banks, E. (2006). Catastrophic risk: Analysis and Management. Wiley Finance.

[2] Birge J.R. and F. Louveaux (1997). Introduction to Stochastic Programming, Springer.

[3] Craighead C.W., J. Blackhurst, M.J. Rungtusanatham and R.B. Handfield, (2007). The Severity of Supply Chain Disruptions: Design Characteristics and Mitigation Capabilities. Decision Sciences 38, 1, 131-156.

[4] Ducapova J., G. Consigli and S.W. Wallace, (2000). Scenarios for Multistage Stochastic Programs. Annals of Operations Research 100, 25-53.

[5] Eppen, G., R. Kipp Martin and L. Schrage (1989). A Scenario Approach to Capacity Planning. Operations Research, 37, pp. 517-527.

[6] Girard, S., A. Martel, J. Berger, A. Boukhtouta, M. Chouinard, A. Ghanmi and A. Guitouni, (2008). Canadian Forces Overseas Supply Network: Strategic Need and Design Methodology, CIRRELT Research Document CIRRELT-2008-34, Université Laval, Canada.

[7] Grossi, P. and H. Kunreuther (2005). Catastrophe modeling: A new approach to managing risk, Springer.

[8] Gutierrez, G.J., P. Kouvelis and A. Kurawala, (1996). A robustness approach to uncapacitated network design problems. European Journal of Operational Research 94, 362-376.

[9] Haimes, Y.Y (2004). Risk modeling, Assessment, and Management. Second edition. Wiley.

[10] Helferich, O.K. and R.L. Cook (2002). Securing the Supply Chain. Council of Logistics Management (CLM).

[11] Hendricks, K.B. and V.R. Singhal (2005). Association between supply chain glitches and operating performance. Management science, vol. 51, No. 5, pp. 695-711.

[12] Kleindorfer, P.R., G.H. Saad (2005). Managing disruption risks in supply chains. Production and Operations Management, 14,1, pp 53-68.

[13] Klibi W., A. Martel and A. Guitouni (2009a). The Design of Robust Value-creating Supply Chain Networks: A Critical Review, European Journal of Operational Research, doi: 10.1016/j.ejor.2009.06.011.

[14] Klibi W., A. Martel and A. Guitouni (2009b). The Impact of Operations Anticipations on the Quality of Supply Network Design Models, CIRRELT Research Document CIRRELT-2009-x, Université Laval, Canada.

[15] Klibi W. and A. Martel (2009). Designing Resilient Supply Networks under Disruptions, CIRRELT Research Document CIRRELT-2009-27, Université Laval, Canada.

[16] Klose A. and A. Drexl (2005). Facility location models for distribution system design. European Journal of Operational Research, 162, pp. 4-29.

[17] Kouvelis P. and G. Yu (1997). Robust discrete optimization and its applications. Kluwer Academic Publishers.

[18] Lee, H. (2004). The Triple-A Supply Chain, Harvard Business Review, October, pp. 102-112.

[19] Lempert, R.J., D.G. Groves, S.W. Popper and S.C. Bankes, (2006). A General, Analytic Method for Generating Robust Strategies and Narrative Scenarios. Management Science 52, 4, 514-528.

[20] Manuj, I. and J. Mentzer, (2008). Global Supply Chain Risk Management, Journal of Business Logistics 29, 1, 133-155.

[21] Martel A. (2005). The Design of Production-Distribution Networks: A Mathematical Programming Approach. In Supply Chain Optimization (J. Geunes and P. Pardalos (ed)). Springer, pp. 265-306.

[22] Mulvey, J.M, R.J. Vanderbei and S.A. Zenios (1995). Robust optimization of large-scale systems, Operations Research 43, pp. 264-281.

[23] Pomper, C. (1976). International Investment Planning: An Integrated Approach. North-Holland.

[24] Rockafellar R.T. (2007). Coherent Approaches to Risk in Optimization Under Uncertainty. Tutorials in Operations Research, INFORMS 2007, 38-61.

[25] Shapiro A., (2003). Monte Carlo Sampling Methods, Chapter 6 in Handbooks in OR. & MS. Vol.10, A. Ruszczynski, A. Shapiro Editors, Elsevier, 2003.

[26] Santoso T., S. Ahmed, M. Goetschalckx and A. Shapiro (2005). A stochastic programming approach for supply chain network design under uncertainty. European Journal of Operational Research, 167, pp. 96-115.

[27] Schneeweiss C. (2003). Distributed Decision Making. Springer, Second edition.

[28] Shapiro A., (2007). Stochastic programming approach to optimization under uncertainty. Mathematical Programming: Series A and B 112, 1, 183-220.

[29] Sheffi, Y. (2005). The resilient enterprise: overcoming vulnerability for competitive advantage. MIT Press Books.

[30] Shell Global Scenarios to 2025 (2005). The future business environment: trends, trade-offs and choices. Shell International Limited (SIL).

[31] Snyder, L.V (2006). Facility location under uncertainty: A review. IIE Transactions 38 (7), 537-554.

[32] Snyder, L.V. and M. S. Daskin (2006). Stochastic p-Robust location problems. IIE Transactions 38 (11), 971-985.

[33] Snyder, L.V., M. P. Scaparra, M. S. Daskin and R. L. Church (2006). Planning for disruptions in supply chain networks. Tutorials in Operations Research, INFORMS 2006, Chap. 9.

[34] Tang, C.S. and B. Tomlin, (2008). The power of flexibility for mitigating supply chain risks. International Journal of Production Economics 116, 12-27.

[35] Tomlin B., (2006). On the Value of Mitigation and Contingency Strategies for Managing Supply Chain Disruption Risks. Management Science 52, 5, 639–657.

[36] Triantaphyllou E., (2000). Multi-Criteria Decision Making Methods: A comparative Study. Springer.

[37] Van der Heijden, K., (2005). Scenarios: The art of strategic conversation. Wiley, 2nd edition.

[38] Vila, D., A. Martel and R. Beauregard. (2007). Taking Market Forces into Account in the Design of Production-Distribution Networks: A Positioning by Anticipation Approach. Journal of Industrial and Management Optimization 3,1, 29-50.

[39] Wagner S.M. and C. Bode (2008). An Empirical Examination of Supply Chain Performance Along Several Dimensions of Risk. Journal of Business Logistics 29, 1, 307-325.