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ROBUST BILEVEL OPTIMIZATION FOR AN OPPORTUNISTIC SUPPLY CHAIN NETWORK DESIGN PROBLEM IN AN UNCERTAIN AND RISKY ENVIRONMENT

This paper introduces the problem of designing a single-product supply chain network in an agile manufacturing setting under a vendor managed inventory (VMI) strategy to seize a new market opportunity. The problem addresses the level of risk aversion of the retailer when dealing with the uncertainty of market related information through a conditional value at risk (CVaR) approach. This approach leads to a bilevel programming problem. The Karush–Kuhn–Tucker (KKT) conditions are employed to transform the model into a single-level, mixed-integer linear programming problem by considering some relaxations. Since realizations of imprecisely known parameters are the only information available, a data-driven approach is employed as a suitable, more practical, methodology of avoiding distributional assumptions. Finally, the effectiveness of the proposed model is demonstrated through a numerical example.

Keywords: *supply chain management, production-distribution planning, conditional value at risk, bilevel programming, robust optimization, KKT conditions*,

1. Introduction

A supply chain (SC) is a network of facilities and distribution options that performs several production-distribution functions to convert raw materials into finished products, and transport them to the final customer. The success of an SC depends strongly on coordinating participants' activities, organizational relationships, and strategic alliances. Thus, supply chain network design (SCND) has become a vital issue regarding the SC and its management. An SCND model aims to construct the structure of a network with a long-term planning horizon and, therefore, it is realistic to expect to face

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uncertainties. The costs of transportation and shortages are imprecisely known parameters, which result from uncertain market demand. Uncertainties reduce the predictability of the performance of an SC and increase risk [1]. Due to the importance of agility in such unpredictable environments, the SC agility has become an important issue in enhancing the performance of the chain. An agile SC is, by definition, capable of operating in a competitive environment and dealing with market opportunities that are continually emerging and changing with uncertainty [2]. A review of the research on agility in SCs and individual enterprises has been provided in [3], and some real-life agile networks, such as the networks of Zara, H&M, the Oberalp group, Calida, C&A, Mango, and Puma, have also been presented in [4].

A manufacturer's agility, as well as its partners' diversity, can enhance the agility of the SC. Therefore, the concept of a virtual supply chain (VSC) emerges as a potential corporation of a group of agile enterprises. Chauhan, Proth [5] introduced the concept of the opportunistic supply chain (OSC) network design to deal with the problem of designing a VSC to take advantage of new market opportunities. Usually, the resulting SC is anything but lean, due to its forecast-based structure. A demand-driven system is capable of obtaining leanness, which in turn enhances the effectiveness of the SC through a vendor managed inventory (VMI) strategy [6]. However, the uncertainty of market information is magnified and makes the SC more vulnerable. A VMI strategy can be organized according to the theory of the Stackelberg games. This theory can be mathematically formulated using bilevel programming (BLP) which is adapted to uncertain systems [7].

The uncertainties of market related information, i.e., on demand and the costs of transportation and shortages, are operational risks of the SC [1]. The importance of taking risk into account, together with the decentralized nature of the SC, makes a robust approach attractive when dealing with the SCND problem under uncertainty [8]. Bertsimas and Sim [9] introduced an approach to constructing a robust linear counterpart of the initial linear problem with uncertainty based on polyhedral uncertainty sets. Natarajan, Pachamanova [10] integrated uncertainty sets into risk measures (RMs). A given function μ is called a RM if it satisfies the axioms of monotonicity and translation in variance. Bertsimas and Brown [11] constructed uncertainty sets based on the concept of coherent risk measures (CRM). A particular RM is called a CRM if it satisfies the additional axioms of convexity and positive homogeneity. A finite number of conditional value at risk (CVaR) measures may generate a class of RMs, called distortion RMs [11]. CVaR is tractable in the context of robust optimization (RO) [12]. It takes into account a decision maker's (DMs) level of risk aversion. Traditionally, the classical IPDP problems obtain the maximum expected profit or the minimum expected cost that are suitable for risk-neutral DMs [15]. However, supporting potential losses resulting from demand uncertainty is very costly for companies. Taking into account risk-aversion preference is, therefore, suitable for such companies [16]. To better define the concept, suppose that a risk-averse DM would like to satisfy the constraint $\mathbf{u}^t\mathbf{x} \geq \psi$ with at least a (1 – α) level of confidence. The DM may enforce $p\left(\mathbf{u}^t\mathbf{x} \geq \psi\right) \geq 1-\alpha$ through a value at risk (VaR) constraint, as in the classical example of the RM defined as $\mathrm{VaR}_\alpha(\mathbf{u}^t\mathbf{x}) \stackrel{\Delta}{=} \inf\left\{b \in \mathrm{R}; \mathrm{p}\left\{\psi + \mathbf{u}^t\mathbf{x} \geq 0\right\} \geq 1-\alpha\right\}$. This approach is computationally complex, due to its non-convex feasible region. CVaR, in contrast, allows a DM to obtain any degree of confidence, (1 – α), while retaining convexity [13]. It transforms the problem into $\max_x \mathrm{CVaR}_\alpha\left(\mathbf{u}^t\mathbf{x}\right)$, where $\alpha \in \left(0,1\right]$reflects the level of risk aversion of the DM [14].

This paper builds on OSC design through integrated production-distribution planning (IPDP) under an uncertain and risky environment. The proposed BLP takes into account the DMs subjective level of risk aversion when dealing with market-related uncertainties. The contributions of this paper are summarized as follows:

- The main objective of this paper is to develop an integrated model of designing an OSC network considering leanness and robustness under an uncertain and risky environment.
- The model leads to a strong linear relationship between the expected cost of the chain and the retailer's level of risk aversion.
- The model aggregates the problem of OSC network design and risk management in a robust manner. Although the model was originally based on coherent risks, it can be adapted to incoherent risks, according to [10].

This paper is organized as follows. A literature review and the motivation of the study are given in Section 2. The problem and its mathematical formulation will be fully described in Section 3. The formulation of the model and method of solution will be introduced in Section 4, and computational results will be presented in Section 5. Finally, conclusions and potential areas of future research will be presented in Section 6.

2. Literature review

Integrating decisions with different functions into a single optimization model is an appropriate approach to formulating a production-distribution system. The IPDP problem is an important issue in supply chain management (SCM). It integrates the two main concerns of SCM to meet demand on time, while attaining minimum cost through an effective production-distribution network [17]. These concerns are, firstly, production planning and control, and, secondly, distribution and logistics. The first area contains the entire manufacturing process, including inventory control, scheduling, and handling materials. The second area, on the other hand, embraces the processes of inventory retrieval, product transportation, and meeting demand [18]. Extensive research has been done using an integrated approach to a production-distribution system. Klibi, Martel [8] and Fahimnia et al. [18] provided a comprehensive review of recent IPDP models and techniques. Kopanos et al. [19] and Yu and Nagurney [20] developed their network-based SC model for a food company. Bilgen and Çelebi [21] studied the problem in a yoghurt production line of multi-product dairy plants within the framework of mixed integer linear programming (MILP). Baghalian, Rezapour [22] addressed a stochastic path-based IPDP problem for a multi-product SC under uncertain demand. Liu and Papageorgiou [23] investigated a capacitated IPDP problem in a global SC using a multi-objective MILP model. Hashim, Nazim [24] employed a BLP approach to an IPDP model in constructing an SC under a fuzzy environment. Golpîra [25] proposed an IPDP to formulate an SCND problem under uncertainty. The resulting robust MILP model aims to minimize the total cost of the network. It takes into account the retailer's level of risk aversion to obtain a more realistic model regarding uncertain demand. Taxakis and Papadopoulos [26] proposed two mixed integer programming models for the production-distribution and inventory planning problem. The number of customers and suppliers, and their demand and capacities were assumed to be known in these models. Khalili, Jolai [27] presented a two-stage scenario-based mixed stochastic-possibilistic programming model for an IPDP problem with a two-echelon SC over a midterm horizon under risk. In their research, possibilistic parameters were introduced to deal with operational risks, while the risk of disruption was addressed by stochastic scenarios. CVaR was employed in their paper to ensure the robustness of the solution. However, the model does not reflect all of the uncertainty in demand. Lalmazloumian, Wong [28] addressed agility and the level of customer service in their research. In their model, a robust, scenario-based approach to optimization was used to deal with uncertainties.

Furthermore, some recent research has been carried out to tackle OSC network design via an IPDP approach. Chauhan et al. [6] used an IPDP approach considering prequalified partners in order to seize a new market opportunity. In their model, the market was characterized by a deterministic forecast over a planning horizon. The objective was to design an SC by selecting one partner from each echelon to meet demand without any backlog. The model was also designed to minimize the production and logistics costs over the given planning horizon. Pan and Nagi [17] extended this model by using an RO approach to deal with uncertain demand. The objective of their study was to choose one partner for each echelon and, simultaneously, choose the inventory level, production plan, and amount of shortages. Pan and Nagi [2] addressed demand from multiple customers as an extension of the model proposed by Pan and Nagi [17]. Selecting multiple companies in each echelon was also permitted to avoid demand remaining unfulfilled. Su, Huang [29] presented an IPDP approach to dealing with the problem of partner selection in SCND. The chain was assumed to operate under a multi-product, multi-stage, multi-production route, multi-machine, and multi-period manufacturing environment. They claimed that a problem often occurs when all of the companies establish partnerships to form a virtual organization in order to capture market opportunities when they arise.

The main motivation of this study was to develop an integrated model for designing an OSC network taking into account robustness, leanness, and agility under an uncertain and risky environment. The resulting bilevel mixed integer linear programming model incorporates the concept of BLP and the problem of designing a single-product OSC network in a robust manner. The model considers the level of risk aversion of the retailer, as well as the uncertainties of a network's downstream costs and customer demand. The resulting network is optimally organized with a set of pre-qualified partners willing to participate to seize a new market opportunity. The final objective is to select one partner for each echelon to achieve the minimum total cost. Thus, the preliminary objective function contains two overall terms, i.e. the deterministic total cost of a suppliers' subsystem and the uncertain total cost of a retailers' echelon. The first term contains a fixed level of production, alliance formation, and transportation costs, and the second term contains uncertain backorder and transportation costs. Reformulation of the second term leads to the BLP problem via the concept of CVaR under a VMI strategy. The Stackelberg leader in the resulting hierarchical IPDP problem is the supplier subsystem and the follower is the retail section. Finally, the model is transformed into a single level mixed integer linear programming problem by using the KKT conditions, which can be solved analytically.

3. Statement of the problem

This paper considers a production-distribution network, for example the network illustrated in Fig. 1, through which an SCN would like to start a new project manufacturing a product in different plants and delivering them to customers through potential transportation links.

In such an organizational web, several virtual companies are considered to perform and transport a single product in a pre-defined production-distribution sequence. Denote the production sequence as $A=\{1, 2, ..., \varphi\}$. The process sequence contains several echelons, $a \in A$, each consisting of several pre-qualified potential partners. Only one operation is accomplished in an echelon. Thus, the echelon contains only one selected company in the final network. The network's structure is a direct network $\Omega = (\Phi, \Theta)$, where Φ denotes the set of potential partners, and Θ defines the set of possible arcs between potential partners. $A_a \subseteq \Phi$ denotes the set of all companies capable of accomplishing operation $a \in A$. N_a indicates the number of potential partners in echelon

$a \in A$. No arc exists between nodes in A_a and all the arcs are directed from a node in A_a, $a \in A$ to a node in A_{a+1}, $a \in A$. This network delivers the final product from the retailer to the customer and, therefore, uncertainty regarding the parameters affects the network at this level. Some retailers are risk-neutral and some are risk-averse.

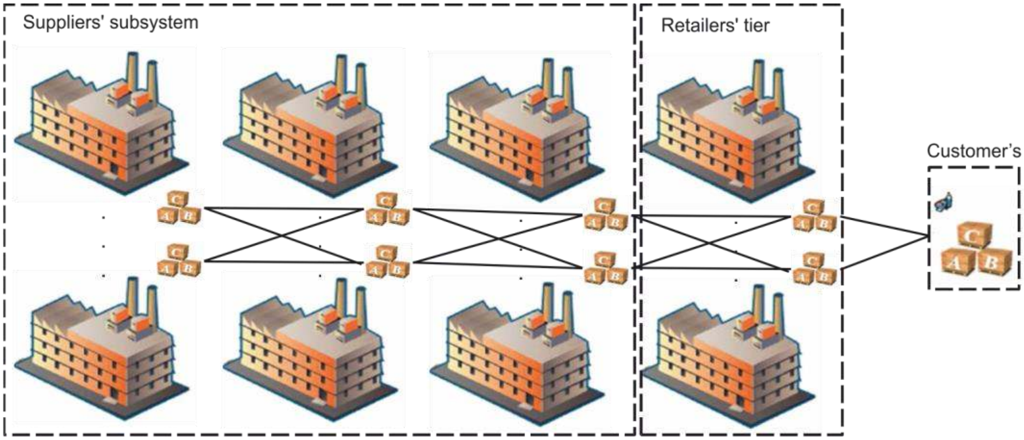

Fig. 1. An illustration of the considered SC

A retailer's level of risk aversion, α, is therefore considered in the formulation of the model. This model aims to design such a VSC in a manner that minimizes the total cost of the network in an uncertain and risky environment. The total cost is the sum of the costs of alliance formation, transportation, manufacturing, and shortages. Moreover, the following assumptions are applied:

- There is no need to consider the inventory or any related costs in the model. This assumption is clearly discussed at the end of Section 4.1.
- The network enters at most only one new market.
- Only one company can be selected in each echelon.
- Shortages are allowed in the last echelon of the network.
- Transportation is assumed to be single-mode.

4. Formulation of the model

Sets and indices

$a \in A = \{1, 2, ..., \varphi\}$ – set of operations/echelons

$i \in I$ – set of available partners for use by the network in echelon a

$j \in J$ – set of available partners for use by the network in echelon $a + 1$

Parameters

N_a – number of pre-qualified potential partners in echelon a

$fc_{i(a)j(a+1)}$ – fixed cost of alliance formation between potential partner i in echelon a and potential partner j in echelon $a+1$

$tc_{i(a)j(a+1)}$ – unit cost of transportation from potential partner i in echelon a to potential partner j in echelon $a+1$

$pc_{i(a)}$ – unit processing cost for potential partner i in tier a

$\theta_{i(\varphi)}$ – available production capacity at potential partner i in the retailers' echelon

m – a very large positive number

β – fill rate parameter

Uncertain parameters

$\tilde{d}$ – uncertain amount of demand

$\tilde{g}_{i(\varphi)}$ – random unit backorder cost for potential partner i in the retailers' echelon

$\tilde{l}_{i(\varphi)}$ – random unit transportation cost from potential partner i in the retailers' echelon to the set of customers

Decision variables

$x_{i(a)j(a+1)}$ – amount of product shipped from potential partner i in echelon a *to* potential partner j in echelon $a+1$

$t_{i(\varphi)}$ – amount of product shipped to customers from potential partner i in the retailers' echelon

$b_{i(\varphi)}$ – amount of backorders at potential partner i in the retailers' echelon

$z_{i(a)}$ – amount of product manufactured at potential partner i in echelon a

$$y_{i(a)j(a+1)} = \begin{cases} 1 & \text{if potential partner } i \text{ in echelon } a \text{ is linked to potential partner } j \\ & \text{in echelon } a+1 \text{ in the network} \\ 0 & \text{otherwise} \end{cases}$$

$$w_{i(a)} = \begin{cases} 1 & \text{if potential partner } i \text{ in echelon } a \text{ is included in the network} \\ 0 & \text{otherwise} \end{cases}$$

4.1. Formulation of the model

The resulting formulation of the MILP for the problem described above is defined by Eqs. (1)–(18):

$$\zeta = \min\left\{\sum_{a=1}^{\varphi-1}\sum_{j=1}^{N_{a+1}}\sum_{i=1}^{N_a} fc_{i(a)j(a+1)}y_{i(a)j(a+1)} + \sum_{a=1}^{\varphi}\sum_{i=1}^{N_a} pc_{i(a)}z_{i(a)} + \sum_{a=1}^{\varphi-1}\sum_{j=1}^{N_{a+1}}\sum_{i=1}^{N_a} tc_{i(a)j(a+1)}x_{i(a)j(a+1)} + \sum_{i=1}^{N_\varphi}\left(\tilde{l}_{i(\varphi)}t_{i(\varphi)} + \tilde{g}_{i(\varphi)}b_{i(\varphi)}\right)\right\} \tag{1}$$

subject to:

$$\sum_{i=1}^{N_a} w_{i(a)} = 1, \quad a = 1, 2, ..., \varphi \tag{2}$$

$$y_{i(a)j(a+1)} \le w_{i(a)}, \ \forall (i, j) \in A, \ a = 1, 2, ..., \varphi - 1 \tag{3}$$

$$y_{i(a)j(a+1)} \le w_{j(a+1)}, \ \forall (i, j) \in A, \ a = 1, 2, ..., \varphi - 1 \tag{4}$$

$$y_{i(a)j(a+1)} \ge w_{i(a)} + w_{j(a+1)} - 1, \ \forall (i, j) \in A, \ a = 1, 2, ..., \varphi - 1 \tag{5}$$

$$z_{i(a)} \le \theta_{i(a)} w_{i(a)}, \ i = 1, 2, ..., N_a, \ a = 1, 2, ..., \varphi \tag{6}$$

$$\sum_{j=1}^{N_{a+1}} x_{i(a)j(a+1)} \le m w_{i(a)}, \ i = 1, 2, ..., N_a, \ a = 1, 2, ..., \varphi - 1 \tag{7}$$

$$\sum_{i=1}^{N_a} x_{i(a)j(a+1)} \le m w_{j(a+1)}, \ j = 1, 2, ..., N_{a+1}, \ a = 1, 2, ..., \varphi - 1 \tag{8}$$

$$\sum_{j=1}^{N_{a+1}} x_{i(a)j(a+1)} - z_{i(a)} = 0, \ i = 1, 2, ..., N_a, \ a = 1, 2, ..., \varphi - 1 \tag{9}$$

$$t_{i(\varphi)} - z_{i(\varphi)} = 0, \ i = 1, 2, ..., N_\varphi \tag{10}$$

$$z_{i(a)} \ge \beta \tilde{d} w_{i(a)}, \ i = 1, 2, ..., N_\varphi, \ a = 1, 2, ..., \varphi \tag{11}$$

$$b_{i(\varphi)} = \tilde{d}w_{i(\varphi)} - t_{i(\varphi)},\ i = 1, 2, ..., N_\varphi \tag{12}$$

$$t_{i(\varphi)} \geq 0,\ \ i = 1, 2, ..., N_\varphi \tag{13}$$

$$b_{i(\varphi)} \geq 0,\ i = 1, 2, ..., N_\varphi \tag{14}$$

$$z_{i(a)} \geq 0,\ \ i = 1, 2, ..., N_a,\ a = 1, 2, ..., \varphi \tag{15}$$

$$x_{i(a)j(a+1)} \geq 0,\ \ \forall(i,\ j) \in A,\ a = 1, 2, ..., \varphi - 1 \tag{16}$$

$$y_{i(a)j(a+1)} \in \{0, 1\},\ \forall(i,\ j) \in A,\ a = 1, 2, ..., \varphi - 1 \tag{17}$$

$$w_{i(a)} \in \{0, 1\},\ \ i = 1, ..., N_a,\ a = 1, 2, ..., \varphi \tag{18}$$

The first term in Eq. (1) describes the total cost of alliance formation. The second term represents the total manufacturing cost of the network. The third term explains the total cost of transportation, excluding the uncertain transportation costs of the retailers. The last term contains the total transportation and backorder costs of the last echelon. Constraints (2)–(5) ensure that the final SC includes only one company from each echelon. According to the set of constraints (6), the amount of production in each company is limited to its capacity. Constraints (7) and (8) impose that goods are only produced by the finally selected companies. Constraints (9) and (10) balance the production-distribution flow. The set of constraints (11) ensures that the uncertain demand is met at a pre-defined rate. The set of constraints (12) represents the fact that the unmet demand is backordered. Constraints (13)–(16) indicate the non-negativity of the decision variables, and constraints (17) and (18) define $y_{i(a)j(a+1)}$ and $w_{i(a)}$ as binary variables. It is noteworthy that unless $w_{i(a)}$ is used, the structural integrity of the network is not guaranteed. Suppose that, for example, $y_{2(1)2(2)} = 1$ and, therefore, $w_{2(1)} = w_{2(2)} = 1$. To ensure the integrity of the network, it is obvious that the potential arc between the second echelon and the third one should be started from the second node of the second echelon, i.e., $y_{2(2)\cdot(3)} = 1$. This is not obtained unless such binary variables are used to describe the nodes of the web. In other words, in the absence of such variables, any arc is feasible when previously selected arcs are not considered. For example, when $y_{2(1)2(2)} = 1$, $y_{3(2)\cdot(3)} = 1$ and $y_{1(2)\cdot(3)} = 1$ are both feasible. This affects the integrity of the network.

According to the aforementioned information, assumption 1 can now be described. Integrating constraints (10)–(12) with constraints (13)–(15) makes the model VMI-

-structured via their demand-driven basics, which in turn leads to a zero level of inventory. For any β > 1, it is obvious from the set of constraints (11) that $z_{i(a)} > \tilde{d}$ and, therefore, the amount of shortages is enforced to be negative, according to constraints (10) and (12). This is inconsistent with the type of $b_{i(\varphi)}$, defined by the set of constraints (14). Thus, β should be equal to or less than one. This means that the inventory level is necessarily equal to zero in the last echelon of the chain. To understand what happens with the inventory at other tiers, additional descriptions are given in Section 4.2.

4.2. Robust mathematical model

The literature provides several definitions of the word robustness. It can be divided into the concepts of robustness of a solution and robustness of a model [30]. The robustness of a solution means that the optimal solution according to a model remains close to optimum for any scenario. The robustness of a model means that the solution remains almost feasible for any realization of the scenarios. Close to optimum means that the solution is near-optimal, while almost feasible means that the penalty function, which is assigned to measure and control the infeasibility, takes a low value. Bertsimas and Brown [11] introduced an approach for constructing uncertainty sets according to CRM for robust linear optimization problems. Discrete probability space, which is motivated by sampling considerations, is directly leveraged to construct a relationship between CRM and corresponding uncertainty sets. This paper employs the same approach as Bertsimas and Brown [11] to deal with the uncertainty of the network's last echelon.

Accordingly, the corresponding robust formulation for Eq. (1) can be defined as:

$$\min\left\{\sum_{a=1}^{\varphi-1}\sum_{j=1}^{N_{a+1}}\sum_{i=1}^{N_a} fc_{i(a)j(a+1)}y_{i(a)j(a+1)} + \sum_{a=1}^{\varphi}\sum_{i=1}^{N_a} pc_{i(a)}z_{i(a)} + \sum_{a=1}^{\varphi-1}\sum_{j=1}^{N_{a+1}}\sum_{i=1}^{N_a} tc_{i(a)j(a+1)}x_{i(a)j(a+1)} + \psi\right\} \tag{19}$$

subject to:

$$\sum_{i=1}^{N_\varphi}(\tilde{l}_{i(\varphi)}t_{i(\varphi)} + \tilde{g}_{i(\varphi)}b_{i(\varphi)}) \geq \psi \tag{20}$$

Let $(\tilde{l}_{i(\varphi)}, \tilde{g}_{i(\varphi)}) = \tilde{\mathbf{U}}_\varphi,\ i = 1, ..., N_{(\varphi)}$ be a matrix describing imprecisely known constraints, where $\tilde{\mathbf{U}}_{(\varphi)} \in \Omega$. Ω is an unknown uncertainty set for $\tilde{\mathbf{U}}_{(\varphi)} \in \mathbb{R}^{1\times 2N_\varphi}$. The concept of RO leads to an optimal solution that is feasible for all realizations of $\mathbf{U}_{(\varphi)}$ based on the set defined according to the concept of CVaR with respect to the DM's risk preferences. Accordingly, suppose that the function $\boldsymbol{\mu}$ is a CRM, and the uncertain vector $\tilde{\mathbf{u}}_{(\varphi)} \in \tilde{\mathbf{U}}_{\varphi}$ is defined as a random vector in $\mathbb{R}^{2N_{\varphi}}$ on a finite probability space. There exists $\mathbf{u}_{s(\varphi)} \triangleq \tilde{\mathbf{u}}_{s(\varphi)}$, where the support of $\tilde{\mathbf{u}}_{(\varphi)}$ is defined by $\Upsilon = \{\mathbf{u}_{1(\varphi)}, ..., \mathbf{u}_{S(\varphi)}\}$, which can be considered as the set of realizations of the problem's uncertain data. A form of constraint (20) which takes risk aversion into account can be defined as $\boldsymbol{\mu}(\tilde{\mathbf{u}}_{(\varphi)}\mathbf{x} - \psi) \le 0$, where $\mathbf{x} = (t_{i(\varphi)}, b_{i(\varphi)})^t$, $i = 1, ..., N_{\varphi}$. This leads to $\mathrm{P}\{\tilde{\mathbf{u}}_{(\varphi)}\mathbf{x} \ge \psi\} \ge 1 - \alpha$ as a non-convex constraint. To deal with the non-convexity of this constraint, an alternative formulation is used in the form of CVaR, which can be defined by Eq. (21).

$$\mathrm{CVaR}_{\alpha}\{\tilde{\mathbf{u}}_{(\varphi)}\mathbf{x} - \psi\} = \underset{\left\{V \in \Delta^{S} : v_s \le 1/(S_{\alpha})\right\}}{-\inf} E_V[\mathbf{u}_{(\varphi)}\mathbf{x}] + \psi \tag{21}$$

in which $\Delta^S \triangleq \{\mathbf{p} \in \mathbb{R}_+^S : \mathbf{e}^t\mathbf{p} = 1\}$ with $\mathbf{e}$ being a vector of ones and $\mathbf{e}_s \triangleq \mathbf{e}/S$. s_α is the number of scenarios remaining after trimming to the level α, $s_\alpha = \lfloor S(1-\alpha) + \alpha \rfloor \approx S(1-\alpha)$, and $x_{(S_\alpha)}$ is the $S_\alpha -$ th best component based on the objective function of the problem. The corresponding CRM, as a combination of CVaR_α for various values of α, can be formulated as $\sum_{s=1}^{S} \theta_s \, \mathrm{CVaR}_{\alpha_s}\{\tilde{\mathbf{u}}_{(\varphi)}\mathbf{x} - \psi\}$, which leads to $\sum_{s=1}^{S} \theta_s \min_{\mathbf{u} \in \prod_{\mathbf{p}^s}(\Upsilon)} \{\mathbf{u}^t_{(\varphi)}\mathbf{x}\} + \psi$ from Eq. (21). $\prod_{\mathbf{p}}(\Upsilon) = \mathrm{conv}\left(\left\{\sum_{s=1}^{S} p_{\sigma(s)}\mathbf{u}_{(\varphi)s} : \sigma \in \rho(S)\right\}\right)$ is called the **b**-permuthall of Υ, and θ_s can be defined by Eq. (22), where $\mathbf{p} = \sum_{s=1}^{S} \theta_s \mathbf{p}_s$ in which $\mathbf{p} \in \Delta^s$ and $p_s \le p_{s+1}$. $\rho(S)$ denotes the set of all permutations of S elements.

$$\theta_s = \begin{cases} s.p_s, & s = S \\ (S-s)(p_{S-s} - p_{S-s+1}), & s = 1, 2, ..., S-1 \end{cases}, \quad \sum_{s=1}^{S} \theta_s = 1 \tag{22}$$

Accordingly, constraint (20) can be defined as:

$$\chi' = -\max\left\{-\left\{\sum_{i=1}^{N_\varphi}\left(\sum_{s=1}^{S} p_{\sigma(s)} l_{i(\varphi)\mathrm{s}}\left(\sum_{k=s}^{S}\theta_k\right) t_{i(\varphi)} + \sum_{s=1}^{S} p_{\sigma(s)} g_{i(\varphi)\mathrm{s}}\left(\sum_{k=s}^{S}\theta_k\right) b_{i(\varphi)}\right)\right\}\right\} + \Psi \tag{23}$$

On the other hand, the demand in constraints (11) and (12) is uncertain. Defining $q_\alpha(\tilde{\mathbf{u}}_{(\varphi)})$ as the α-quantile of $\tilde{\mathbf{u}}_{(\varphi)}$, it can be derived from [31] and Eq. (21) that $\mathrm{CVaR}_\alpha = \mathrm{E}[\mathbf{U}_{(\varphi)} : \mathbf{U}_{(\varphi)} \le q_\alpha(\tilde{\mathbf{U}}_{(\varphi)})]$ for all realizations of $\mathbf{U}_{(\varphi)}$ ($\mathbf{U}_{(\varphi)} = \{\mathbf{u}_{(\varphi)1}, ..., \mathbf{u}_{(\varphi)s}\}$) is given by

$$\mathrm{CVaR}_\alpha = \frac{1}{s_\alpha} \sum_{s=1}^{\lfloor s_\alpha \rfloor} d_{(s)} - \left(\frac{s_\alpha - \lfloor s_\alpha \rfloor}{\lfloor s_\alpha \rfloor} \right) d_{(\lceil s_\alpha \rceil)} \tag{24}$$

Taking into account Eqs. (19), (23), and (24), the model is written as a BLP problem, which was first introduced by Von Stackelberg in 1934 to model the leader-follower game. The objective of the player at the upper level is indicated by Eq. (19), while the objective function of the player at the lower level is given by Eq. (23). Constraints (10), and (12)–(14) are embedded in the model's lower level. Constraints (2), (11), (15), and (18) are separated into two subsets, i.e. subsets of upper and lower level constraints, each of which is embedded in the appropriate level. The other constraints are embedded in the model's upper level. In such a game, the leader makes the first move, taking into account that the follower reacts in an optimal way to the leader's choice, and then the follower reacts optimally to the leader's action. Thus, it is logically obvious that the leader should anticipate the follower's response, in order to optimize its objective function. This can provide some additional explanations about why assumption 1. $z_{i(\varphi)}$ is obtained directly from the model's lower level, which is completely described at the end of Section 4.1. The amount of goods produced in the suppliers' subsystem is consequently calculated from the amount $z_{i(\varphi)}$ that is predefined directly from market demand. This is because of the structure of the BLP, which in turn implements a VMI strategy according to the set of constraints (11). Therefore, the level of inventory is enforced to be equal to zero in the entire SCN and therefore there is no need to consider the inventory or any related costs in the model.

The resulting BLP problem can be solved using its KKT conditions, which is an appealing way of dealing with general BLP problems. In this way, the lower level problem can be replaced by its Karush–Kuhn–Tucker (KKT) conditions to obtain the corresponding single level problem. This approach is applicable when the lower-level problem is convex and regular. However, the lower level problem of the model proposed in this paper is not convex with respect to the variables $w_{i(\varphi)}$ defined by constraints (18). Accordingly, the term $mw_{i(\varphi)}(1 - w_{i(\varphi)})$ is added to the corresponding objective function to penalize deviance of $w_{i(\varphi)}$ from 0 or 1. Thus, Eq. (23) is transformed into Eq. (25), and the variables $w_{i(\varphi)}$, $i = 1, ..., N_a$ are defined by the set of constraints (26). After applying this relaxation, the KKT conditions for the model's lower level problem are obtained from equations (27) to (54). The symbol $\perp$, in the constraints, is used to denote the orthogonal relationship which exists between the follower's complementary conditions.

$$\chi = -\max\left\{-\left\{\sum_{i=1}^{N_\varphi}\left(\sum_{s=1}^{S} p_{\sigma(s)} l_{i(\varphi)s}\left(\sum_{k=s}^{S}\theta_k\right)t_{i(\varphi)}\right.\right.\right.$$

$$\left.\left.\left.+\sum_{s=1}^{S} p_{\sigma(s)} g_{i(\varphi)s}\left(\sum_{k=s}^{S}\theta_k\right)b_{i(\varphi)}\right)\right\} - m w_{i(\varphi)}(1-w_{i(\varphi)})\right\} + \psi \tag{25}$$

$$0 \le w_{i(\varphi)} \le 1,\ i = 1, ..., N_a \tag{26}$$

$$t_{i(\varphi)} - z_{i(\varphi)} \le 0 \perp \lambda_i^1 \ge 0,\ \ i = 1, 2, ..., N_\varphi \tag{27}$$

$$-t_{i(\varphi)} + z_{i(\varphi)} \le 0 \perp \lambda_i^2 \ge 0,\ \ i = 1, 2, ..., N_\varphi \tag{28}$$

$$-z_{i(\varphi)} + \beta\left(\frac{1}{s_\alpha}\sum_{s=1}^{\lfloor s_\alpha \rfloor} d_{(s)} - \left(\frac{s_\alpha - \lfloor s_\alpha \rfloor}{\lfloor s_\alpha \rfloor}\right) d_{(\lceil s_\alpha \rceil)}\right) w_{i(\varphi)} \le 0 \perp \lambda_i^3 \ge 0,\ i = 1, 2, ..., N_\varphi \tag{29}$$

$$b_{i(\varphi)} + t_{i(\varphi)} - \left(\frac{1}{s_\alpha}\sum_{s=1}^{\lfloor s_\alpha \rfloor} d_{(s)} - \left(\frac{s_\alpha - \lfloor s_\alpha \rfloor}{\lfloor s_\alpha \rfloor}\right) d_{(\lceil s_\alpha \rceil)}\right) w_{i(\varphi)} \le 0 \perp \lambda_i^4 \ge 0,\ i = 1, 2, ..., N_\varphi \tag{30}$$

$$-b_{i(\varphi)} - t_{i(\varphi)} + \left(\frac{1}{s_\alpha}\sum_{s=1}^{\lfloor s_\alpha \rfloor} d_{(s)} - \left(\frac{s_\alpha - \lfloor s_\alpha \rfloor}{\lfloor s_\alpha \rfloor}\right) d_{(\lceil s_\alpha \rceil)}\right) w_{i(\varphi)} \le 0 \perp \lambda_i^5 \ge 0,\ i = 1, 2, ..., N_\varphi \tag{31}$$

$$\sum_{i=1}^{N_\varphi} w_{i(\varphi)} \le 1 \perp \lambda_i^6 \ge 0,\ i = 1, 2, ..., N_\varphi \tag{32}$$

$$-\sum_{i=1}^{N_\varphi} w_{i(\varphi)} \le -1 \perp \lambda_i^7 \ge 0,\ \ i = 1, 2, ..., N_\varphi \tag{33}$$

$$-t_{i(\varphi)} \le 0 \perp \lambda_i^8 \ge 0,\ \ i = 1, 2, ..., N_\varphi \tag{34}$$

$$-b_{i(\varphi)} \le 0 \perp \lambda_i^9 \ge 0,\ i = 1, 2, ..., N_\varphi \tag{35}$$

$$-z_{i(\varphi)} \le 0 \perp \lambda_i^{10} \ge 0,\ i = 1, 2, ..., N_\varphi \tag{36}$$

$$-w_{i(\varphi)} \le 0 \perp \lambda_i^{11} \ge 0,\ i = 1, 2, ..., N_\varphi \tag{37}$$

$$w_{i(\varphi)} \le 1 \perp \lambda_i^{12} \ge 0,\ i = 1, 2, ..., N_\varphi \tag{38}$$

$$\lambda_i^4 - \lambda_i^5 - \lambda_i^9 = -\sum_{s=1}^{S} p_{\sigma(s)} l_{i(\varphi)\mathrm{s}} \left(\sum_{k=s}^{S} \theta_s \right),\ i = 1, 2, ..., N_\varphi \tag{39}$$

$$\lambda_i^1 - \lambda_i^2 + \lambda_i^4 - \lambda_i^5 - \lambda_i^8 = -\sum_{s=1}^{S} p_{\sigma(s)} b_{i(\varphi)\mathrm{s}} \left(\sum_{k=s}^{S} \theta_s \right),\ i = 1, 2, ..., N_\varphi \tag{40}$$

$$-\lambda_i^1 + \lambda_i^2 - \lambda_i^3 - \lambda_i^{10} = 0,\ i = 1, 2, ..., N_\varphi \tag{41}$$

$$\beta\left(\frac{1}{s_\alpha} \sum_{s=1}^{\lfloor s_\alpha \rfloor} d_{(s)} - \left(\frac{s_\alpha - \lfloor s_\alpha \rfloor}{\lfloor s_\alpha \rfloor} \right) d_{(\lceil s_\alpha \rceil)} \right) \lambda_i^3 - \frac{1}{s_\alpha} \sum_{s=1}^{\lfloor s_\alpha \rfloor} d_{(s)} - \left(\frac{s_\alpha - \lfloor s_\alpha \rfloor}{\lfloor s_\alpha \rfloor} \right) d_{(\lceil s_\alpha \rceil)} \lambda_i^4$$
$$+\left(\frac{1}{s_\alpha} \sum_{s=1}^{\lfloor s_\alpha \rfloor} d_{(s)} - \left(\frac{s_\alpha - \lfloor s_\alpha \rfloor}{\lfloor s_\alpha \rfloor} \right) d_{(\lceil s_\alpha \rceil)} \right) \lambda_i^5 + \lambda_i^6 - \lambda_i^7 + \lambda_i^{11} - \lambda_i^{12} = 0,\ i = 1, 2, ..., N_\varphi \tag{42}$$

$$\lambda_i^1 (t_{i(\varphi)} - z_{i(\varphi)}) = 0\ ,\ i = 1, 2, ..., N_\varphi \tag{43}$$

$$\lambda_i^2 (-t_{i(\varphi)} + z_{i(\varphi)}) = 0\ ,\ i = 1, 2, ..., N_\varphi \tag{44}$$

$$\lambda_i^3 \left(-z_{i(\varphi)} + \beta \left(\frac{1}{s_\alpha} \sum_{s=1}^{\lfloor s_\alpha \rfloor} d_{(s)} - \left(\frac{s_\alpha - \lfloor s_\alpha \rfloor}{\lfloor s_\alpha \rfloor} \right) d_{(\lceil s_\alpha \rceil)} \right) \right) = 0,\ i = 1, 2, ..., N_\varphi \tag{45}$$

$$\lambda_i^4 \left(b_{i(\varphi)} + t_{i(\varphi)} - \left(\frac{1}{s_\alpha} \sum_{s=1}^{\lfloor s_\alpha \rfloor} d_{(s)} - \left(\frac{s_\alpha - \lfloor s_\alpha \rfloor}{\lfloor s_\alpha \rfloor} \right) d_{(\lceil s_\alpha \rceil)} \right) \right) = 0,\quad i = 1, 2, ..., N_\varphi \tag{46}$$

$$\lambda_i^5 \left(-b_{i(\varphi)} - t_{i(\varphi)} + \left(\frac{1}{s_\alpha} \sum_{s=1}^{\lfloor s_\alpha \rfloor} d_{(s)} - \left(\frac{s_\alpha - \lfloor s_\alpha \rfloor}{\lfloor s_\alpha \rfloor} \right) d_{(\lceil s_\alpha \rceil)} \right) \right) = 0,\ i = 1, 2, ..., N_\varphi \tag{47}$$

$$\lambda_i^6\left(\sum_{i=1}^{N_\varphi} w_{i(\varphi)}-1\right)=0,\ i=1,2,\ldots,N_\varphi \tag{48}$$

$$\lambda_i^7\left(-\sum_{i=1}^{N_\varphi} w_{i(\varphi)}+1\right)=0,\ i=1,2,\ldots,N_\varphi \tag{49}$$

$$\lambda_i^8(-t_{i(\varphi)})=0,\ i=1,2,\ldots,N_\varphi \tag{50}$$

$$\lambda_i^9(-b_{i(\varphi)})=0,\ i=1,2,\ldots,N_\varphi \tag{51}$$

$$\lambda_i^{10}(-z_{i(\varphi)})=0,\ i=1,2,\ldots,N_\varphi \tag{52}$$

$$\lambda_i^{11}(-w_{i(\varphi)})=0,\ i=1,2,\ldots,N_\varphi \tag{53}$$

$$\lambda_i^{12}(w_{i(\varphi)}-1)=0,\ i=1,2,\ldots,N_\varphi \tag{54}$$

Even under suitable assumptions regarding convexity, the above mathematical program is not easy to solve, due mainly to the non-convexities that occur in the complementarity and Lagrangian constraints, i.e. Eqs. (43)–(54). Several researchers suggest complete enumeration algorithms to deal with such a condition, see e.g., [32]. However, applying complete enumeration to find all the solution points for the model proposed in this paper is a time-consuming procedure. It is therefore necessary to introduce an appropriate relaxation approach to overcome this complexity. In this way, given the binary variable $\kappa_{\kappa i} = (0, 1)$, $\kappa = 1, ..., 12$, $i = 1, 2, ..., N_\varphi$, each non-linear constraint is substituted by two linear ones. For instance, constraint (52) is relaxed as follows:

$$\lambda_i^{10}\le m\kappa_{10i},\ i=1,2,\ldots,N_\varphi \tag{55}$$

$$(-z_{i(\varphi)})\le m(1-\kappa_{10i}),\ i=1,2,\ldots,N_\varphi \tag{56}$$

5. Computational results, discussion and sensitivity analysis

The problem considers 48 potential partners in a 4-tier network as an organizational web to seize a new market opportunity. It can be shown (Fig. 2) that there exist 20 736 feasible routes in the network. The data for this example are illustrated in Table 1. CPLEX 9.0 is executed on a PC that has a 2.20 GHz Intel (R) Core (TM)2 Duo CPU and 3.0 G RAM to solve the resulting MILP problem. The mean time consumed to solve the problem is 174 s.

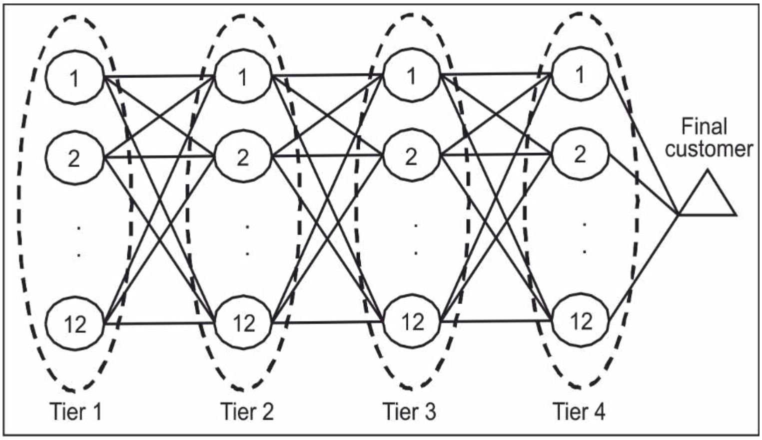

Fig. 2. The organizational web for the numerical example

Table 1. Data used in the problem

Data type	Distribution
Demand	Unif (50, 600)
Unit cost of transportation	Unif (10, 30)
Fixed cost of forming an alliance	Unif (1000, 5000)
Unit cost of production	Unif (20, 60)
Unit cost of backorder	Unif (10, 30)
Production capacity	Unif (500, 700)

The results illustrated in Fig. 3 clearly demonstrate the sensitivity of the optimal value of the objective function to the retailer's level of risk aversion, α, while Fig. 4 illustrates the sensitivity of the network's structure to the parameter α. Figure 4 shows the four different logistic chains chosen in response to α. This figure illustrates that the chain 2-1-1-1 is selected when the retailer's level of risk aversion is sufficiently large. The chain 2-12-12-12 is the optimal chain when the retailer's level of risk aversion is sufficiently small. The retailer assigned to node 1 in the retailer tier is risk-neutral, and makes its decision based on expected profit. On the other hand, the retailer assigned to node 12 in the retailer tier is risk-averse, and makes its decision based on worst possible case. A retailer's readiness to sacrifice mean profit to avoid risk increases, while the parameter α decreases. As a result, the demand of a risk-averse retailer decreases. That is to say, the retailer itself decreases the level of production and the expected total cost of the chain, which is clearly demonstrated in Fig. 3.

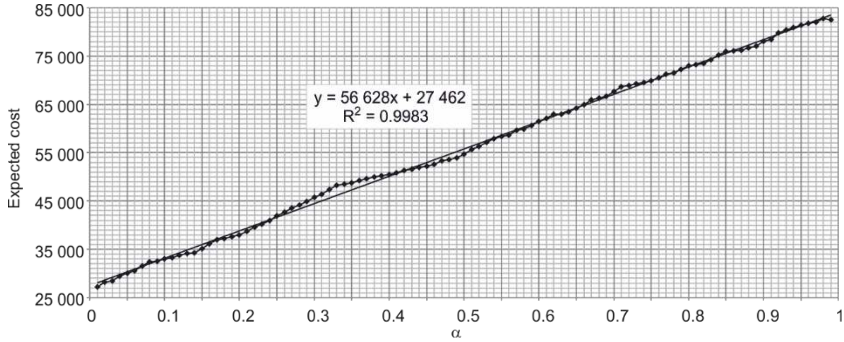

Fig. 3. Expected costs with respect to α

This is consistent with constraints (11) and Eq. (23). According to Eq. (23), a risk-averse retailer would like to minimize its expected cost, while it would like to satisfy constraints (11) with at least $1 - \alpha$ level of confidence. In other words, the retailer could enforce $p\,(z_{i(a)} \geq \beta \tilde{d}w_{i(a)}) \geq 1 - \alpha$ for any value of α. It is obvious that a smaller value of retailer's level of risk aversion leads to a higher value of $1 - \alpha$. This means that the retailer would like to be at a higher level of confidence which results from a small amount of demand, according to constraints (11). Not only does Fig. 3 illustrate the logical relationship between the expected costs and the retailer's level of risk aversion, but also it provides some more details about this relationship. It clearly indicates a strong almost linear relationship ($R^2 = 0.9983$) between the expected total cost and the values of α.

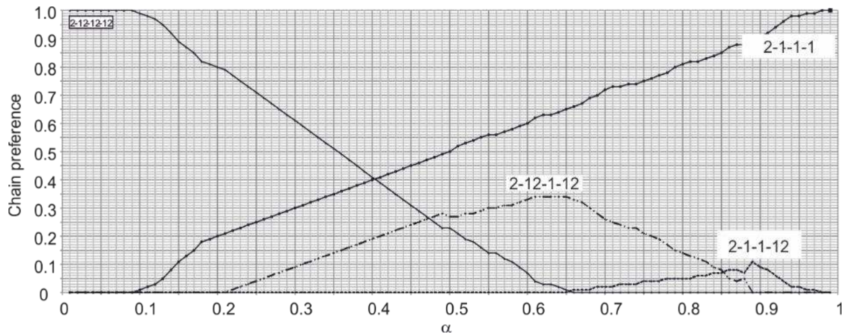

Fig. 4. Optimal chains and their preferences with respect to α

Figure 4 shows the effect of α on the chain's preferences that in turn can be used to measure the robustness of the model according to the results illustrated in Fig. 3. It is noteworthy that in order to validate the robustness of the model, the preference for the preferred chain should show a clear relationship with α. Thus, the expected preferences of the chains, illustrated in Fig. 4, indicate that the model is robust. It is noteworthy that only 4 routes are selected from the 20 736 possible ones, which also indicates that the model is robust, by itself. On the other hand, as the level of risk aversion increases the cost variability ratio is logically decreases, while the expected total cost increases regarding the SCs greater production level.

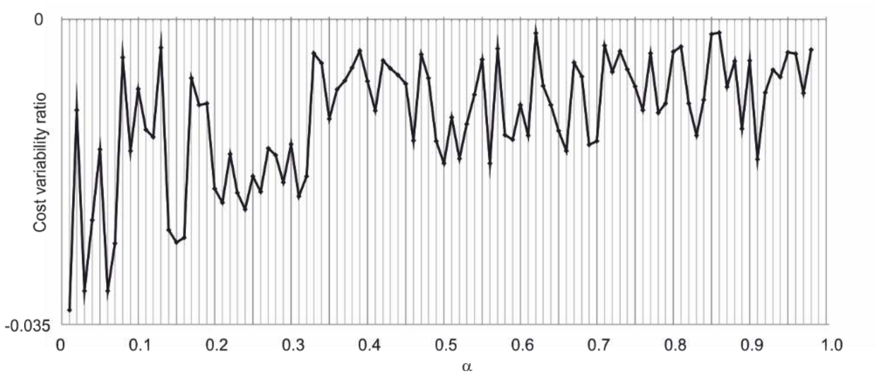

Fig. 5. Variability of expected cost with respect to α

Figure 4 illustrates the sensitivity of the variability of the costs to the retailer's level of risk aversion. Therefore, the retailer makes a trade-off between the network's expected cost and its variability with respect to its level of risk aversion. On the other hand, the figures show that the variability of the expected cost is small in comparison to the corresponding expected total cost for any value of α. These results also indicate that the solution is robust.

6. Conclusion and future potential

The main motivation of this study was to develop an integrated design for an SCN taking into account robustness, leanness, and agility, under an uncertain and risky environment. The research aimed to provide an analytic framework for such a network, which is absent in the literature. The resulting robust model successfully considers uncertain backorder and transportation costs under a VMI strategy using binary variables and well-defined constraints. It guarantees a certain level of customer service and achieves the optimal total cost for the chosen chain. The network is organized from pre-qualified partners in an organizational web to seize a new market opportunity. To deal with the uncertainty in demand and the risky environment, a CVaR approach is successfully employed using a data driven procedure based on a retailer's level of risk aversion. This approach provides the appropriate aggregation of the problem of designing an OSC network with hazard management. To analytically solve the model, i.e. obtain a globally optimal solution using the KKT conditions, some relaxations are considered in the model. The resulting single-level problem is an MILP problem that may be easily solved.

The computational results make evident the desirable properties of the model as follows:

• The level of risk aversion of a retailer has a significant impact on the structure of the SC.

• Integrating a CVaR approach and the BLP concept with a VMI strategy makes the SC well-organized in a robust manner, taking into account leanness.

• Using CVaR to deal with uncertainties leads to a strong near linear relationship between the retailer's level of risk aversion and the final expected total cost of the chain. This enables the DM to establish a trade-off between the total cost of the chain and the level of the retailer's risk aversion.

To encourage future research on the basis of the results presented here, the following are some potential research areas. It is obvious that the proposed framework is static, but it is more realistic that the DM wants the SCN to evolve over time. In this way, an inventory of raw materials and products, and related lead times with certain/uncertain costs might need to be considered in such a model. Another area of future research is to design a model for a multi-product SCN taking into account different modes of transportation. This may significantly enhance the applicability of the model, particularly to global SCNs. Applying multi-level optimization to deal with other sources of risk may be another direction for future research. The model presented here uses the framework of bilevel programming with a particular concept of CVaR to deal with uncertainties regarding the costs. It is clear that the uncertainty regarding demand could also be handled in the same way. This may transform the model to three-level optimization. Other sources of uncertainties (e.g. exchange rate, tax, travel times, and price) could also be dealt with to obtain a more realistic model. Another future direction could be addressing some other aspects, such as greenness and service functions. This may lead to bilevel multi-objective programming, which has been extensively reviewed by Lu, Han [33].

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