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# Marrying supply chain sustainability and resilience: A match made in heaven

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ABSTRACT

Sustainable supply chain management has become an integral part of corporate strategy for virtually every industry. However, little is understood about the broader impacts of sustainability practices on the capacity of the supply chain to tolerate disruptions. This article aims to explore the sustainability–resilience relationship at the supply chain design level. A multi-objective optimization model featuring a sustainability performance scoring method and a stochastic fuzzy goal programming approach is developed that can be used to perform a dynamic sustainability tradeoff analysis and design a "resiliently sustainable" supply chain. Important managerial and practical insights are obtained from an empirical case study.



## 1. Introduction

Sustainability has become a major buzzword in business vocabulary in recent years. Supply chain (SC) professionals are in an excellent position to broadly impact sustainability practices through the integration of economic, environmental and social goals when designing and planning the SCs. More organizations are realizing the strategic importance of sustainability investments. In this environment, the development and availability of analytical models and decision-support tools can help organizations make more effective and informed decisions. To respond to this call, academic research on sustainable SC design and management has seen substantial development over the past two decades (Brandenburg et al., 2014; Fahimnia et al., 2015a,b; Seuring, 2013). Most of the efforts to achieve SC sustainability have been predominantly directed at reducing environmental burdens of the SC, commonly measured in terms of greenhouse gas (GHG) emissions and resource consumption (Fahimnia et al., 2014b). The social sustainability aspect has focused more on the potential damage to human health and the community/society at large (Boukherroub et al., 2015).

Despite the growing efforts on sustainable SC design and management, the broader impact of sustainability interventions on the overall resilience of the SC has remained unexplored. Sustainable SC management in an environment characterized by frequent unavoidable disruptions necessitates sustainability modeling and analysis that can accommodate this complexity and dynamism. Static sustainability analysis[2] is simplistic because the economic and non-economic sustainability performance of a SC can be affected by disruptive events such as supply disruptions. This calls for management approaches and optimization

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[2] "*Static sustainability analysis*" refers to the study of SC sustainability performance in business-as-usual, situations, disregarding the likelihood of external disruptions occurring. "*Dynamic sustainability analysis*" studies the SC performance in both business-as-usual and disruption situations.

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techniques to develop resilient and sustainable SCs, or what we term as "*resiliently sustainable SCs*", wherein sustainability performance remains unaffected or slightly affected in disruptions.

"*SC resilience*" can be defined as the capacity of a SC to absorb disturbances and retain its basic function and structure in the face of disruptions (Pettit et al., 2010; Walker and Salt, 2006). Given the increasing frequency and intensity of natural disasters as well as the continuous stream of anthropogenic catastrophes (Jabbarzadeh et al., 2014), the riskiest thing a company can do is to have no contingency plan. A general consensus is to improve the SC resilience given the demonstrated quantifiable benefits that can be obtained from investments in resilience (Cutter, 2013). We aim in this article to investigate how SC sustainability analysis and resilience improvement can be coupled for developing resiliently sustainable SCs.

Discussions of marrying sustainability science with resilience theory are at a relatively early stage of development (Derissen et al., 2011; Fiksel, 2006; Perrings, 2006; Walker and Salt, 2006). At the organizational level, the incorporation of sustainability and resilience measures into SC practices pose significant management and modeling challenges. Some of these challenges that we tackle in some form in this article include identifying, quantifying and weighting of the sustainability and resilience performance measures, and exploring the real-world application of the associated modeling efforts. Essentially, our primary aim is to answer a critical question: under what circumstances is it possible for a SC to concurrently sustain economic growth, minimize social and environmental impacts, and yet be resilient to disruptions? We limit the boundary of our study and investigation to the suppliers' sustainability performance and its impact on the general SC resilience. An explicit focus on upstream SC operations is of paramount importance due to the global price-based sourcing trends forcing organizations to purchase from cheaper but "less reliable" and "less sustainable" suppliers. This is exemplified in our empirical case study of a sportswear manufacturing company where the primary concerns are the sustainability performance and reliability of its synthetic fiber suppliers.

The remainder of this article is continued in Section 2 by a review of the related SC modeling literature and the introduction of an important research gap which this study will address. Problem description, the mathematical model and solution approach are then presented in Section 3. An execution of the model using real data from a multinational sportswear clothing company is presented in Section 4. Numerical results from static and dynamic sustainability tradeoff analyses and related discussions are presented in this section. Section 5 includes a summary of the research contributions and implications, model and study limitations, and future research directions.

## 2. Review of the related literature

Given the explicit focus of this study on integrating SC sustainability and resilience, in the following sections we first provide a review of the modeling efforts in these two areas and will then draw upon those to position our work in the nexus of these two topics.

### *2.1. Measuring and modeling SC sustainability*

Research in the area of SC sustainability has tended to focus on empirical and conceptual studies with only a scant, but rapidly growing, number of articles published on analytical modeling and quantitative analysis of the related problems (Brandenburg et al., 2014; Fahimnia et al., 2015a,b). Most of these modeling efforts locate within the context of green or environmentally sustainable SC which involves the incorporation of economic and environmental sustainability measures when designing and managing SCs (Fahimnia et al., 2014a). Minimization of GHG emissions has been the most popular environmental objective (Benjaafar et al., 2013; Tang and Zhou, 2012) which is not surprising given the global emission reduction forces and environmental regulatory mandates to tackle climate change. Green SC modeling efforts have been expanding in the following six directions:

(1) optimization models for strategic SC design seeking to balance SC cost and carbon emissions (Brandenburg, 2015; Elhedhli and Merrick, 2012; Rezaee et al., in press; Wang et al., 2011);
(2) tactical and operational planning tools for SC cost-emission tradeoff (Fahimnia et al., 2013a, 2014a; Zakeri et al., 2015);
(3) design and planning of closed-loop SCs focusing on cost/emission performance of the forward and reverse networks (Chaabane et al., 2011, 2012; Fahimnia et al., 2013b);
(4) integration of life cycle assessment principles for environmental impact assessment of SCs (Bojarski et al., 2009; Hugo and Pistikopoulos, 2005);
(5) development and application of multiple performance measures (more than just emissions) for green SC design and management (Fahimnia et al., 2014b; Nagurney and Nagurney, 2010; Pinto-Varela et al., 2011; Pishvaee and Razmi, 2012); and
(6) introducing and investigating environmental policy instruments in SC planning and optimization (Diabat et al., 2013; Fahimnia et al., in press; Zakeri et al., 2015).

Apart from studies on green SC design and management, there is only a handful of modeling efforts incorporating performance measures in three sustainability dimensions. The fact that a consensus on measuring and reporting SC social sustainability does not exist (Varsei et al., 2014) is the primary reason for research scarcity in this space. Pishvaee et al. (2012) use the number of jobs created, the use of hazardous material, and the labor working condition as social metrics in a sustainable

SC design model. You et al. (2012) present a multi-objective model for design of a cellulosic ethanol SC using SC cost, life cycle GHG emissions and the number of local jobs created per unit expenditure as economic, environmental and social performance measures, respectively. A multi-objective possibilistic programming model is presented by Pishvaee et al. (2014) to design a sustainable SC network using ReCiPe 2008 (Goedkoop et al., 2009) to estimate the environmental impacts of the SC and GSLCAP (Benoıt and Mazijn, 2009) to assess the SC's social impact in three areas: created job opportunities, damage to workers' and customers' health, and local development. More recently, Zhang et al. (2014) studied the optimal design and planning of a SC considering cost, GHG emissions, and lead-time (as a measure of SC responsiveness) as economic, environmental and social performance metrics, respectively. Boukherroub et al. (2015) study a tactical SC planning problem in which proximity of employees to production sites and employment stability (transfer of employees between sites rather than laying them off) are used as social performance measures.

As can be seen in these studies, the selection of environmental and social measures to incorporate into SC models is industry and problem specific. Comprehensive lists of these measures can be obtained from some of the past studies (e.g., Hassini et al. (2012)) and from those metrics adopted by the existing environmental impact assessment methods such as IMPACT 2002+ (Jolliet et al., 2003), Eco-indicator 99 (Goedkoop et al., 2009), and CML2001 (Guinèe et al., 2001) as well as the social performance standards and guidelines of SA8000 (SAI, 2008), GRI (GRI, 2011) and GSLCAP (Benoıt and Mazijn, 2009).

Given the broad scope and extensive coverage of these metrics, an effort will then need to be made to refine the lists to only those that (1) are more relevant to SC design and management decisions, (2) are quantifiable in some form, and (3) account for the major characteristics of the concerned industry and problem. An illustration of such effort will be given in our empirical case study investigation in Section 4.

### 2.2. Measuring and modeling SC resilience

The recent global financial crises and the increasing frequency of natural and anthropogenic catastrophes indicate the need for organizations to hedge their SCs against major disruptions. A common approach is to design more "robust" SCs that can remain unaffected or less affected in the face of major disruptions (Christopher and Peck, 2004; Esmaeilikia et al., 2014b; Snyder et al., 2012). Today's SCs also need to be more "flexible/agile" to be able to quickly respond to regular demand fluctuations, variations in supply and lead-time, and exchange rate volatility. Such interruptions are usually managed at the tactical planning level (intermediate timing terms) through building more flexibility into the SC (Esmaeilikia et al., 2014a; Jabbarzadeh et al., in press). The latter is outside the scope of this study, and hence we here provide a review of the related modeling approaches that have been used to measure and account for disruption risks at the strategic SC design level—the explicit scope of this study. General reviews of the literature of SC risk and resilience have been recently completed by Fahimnia et al., 2015a,b and Heckmann et al. (2015).

An expected value approach has been a popular methodologies to account for SC resilience. The approach has been broadly used in making mathematically sound decisions on investment and prioritizing resilience building options by assigning weights to future events and calculating the expected value of different disruption scenarios. Snyder and Daskin (2005) were early proponents to use an expected value approach for the incorporation of disruption risks into a facility location problem. Aryanezhad et al. (2010) and Chen et al. (2011) extend this model for joint location-inventory decision making assuming equal and independent likelihood for a disruption to occur. Unequal disruption probabilities have also been studied by a number of other researchers (Berman et al., 2007; Cui et al., 2010; Li et al., 2013; Li and Ouyang, 2010; Lim et al., 2010; O'Hanley et al., 2013). SC design models for situations with dependent disruption probabilities have been investigated by Shen et al. (2011), Jabbarzadeh et al. (2012), and Garcia-Herreros et al. (2014).

Arguably, value-at-risk (VaR) and conditional value-at-risk (CVaR) have been the two most popular measures for SC resilience. Sawik (2011) presents portfolio methodologies for the selection of suppliers in the presence of SC disruption risks and applies VaR and CVaR to account for the risk of supply disruptions. Sawik (2013b) enhances this approach for a combined selection and protection of suppliers and order quantity allocation. The protection decisions include the selection of suppliers to be protected against disruptions and the allocation of emergency inventory to be pre-positioned at the protected suppliers so as to maintain uninterrupted supply when disruptions occur. Using the same methodology, (Sawik, 2013a); Sawik (2014a,b, 2015) develops stochastic mixed integer programming models to integrate supplier selection and customer order scheduling under risk of disruption. The CVaR measure was also utilized by Madadi et al. (2014) to measure and quantify disruption risks in a pharmaceutical SC design problem.

Worst-case approaches and robustness measures have also been utilized in optimization models for design of resilient SCs. Medal et al. (2014) examine the integration of facility location and hardening decisions, aiming to minimize the maximum distance between a demand point and its closest located facility in disruptions. A multi-objective optimization approach has been presented by Hernandez et al. (2014) seeking to tradeoff the total weighted travelled distance before and after disruptions. Without the need to elicit facility failure probabilities, the proposed approach allows a decision maker to understand the impact of opening facilities on system robustness. Baghalian et al. (2013) consider the solution robustness measure introduced by Mulvey et al. (1995) to design a robust SC network. More recently, Peng et al. (2011) present a SC design model using a $p$-robustness criterion that minimizes the SC cost in business-as-usual situation in a way that the solution has a relative regret of no more than $p$ in each disruption scenario.

Apart of the above studies with a general aim of protecting a network against disruptions, there have been some efforts focusing on the ability of networks to "bounce back" in disruptive events. Pant et al. (2014) present a modeling paradigm for quantifying system resilience, primarily as a function of vulnerability (the adverse initial impact of a disruption) and recoverability (the speed of system recovery). Stochastic measures of resilience, including Time to Total System Restoration, Time to Full System Service Resilience, and Time to $\alpha$%-Resilience are introduced in this study. Baroud et al. (2014b) study the application and usefulness of these measures in a waterway network planning problem. Building on the prior studies, Baroud et al. (2015) introduce a stochastic approach to compute three resilience cost metrics including the loss of service cost, the total network restoration cost, and the cost of interdependent impacts. Same authors also present two approaches to measure the importance of component contribution to network resilience as a function of stochastic vulnerability and recoverability (Baroud et al., 2014a). An optimization method is also developed to determine the order in which disrupted links should be recovered for improved resilience. In this domain, Losada et al. (2012) present a model to speed up recovery time after disruptions and protecting an uncapacitated median type facility network against worst-case losses.

### *2.3. Marrying SC sustainability and resilience: A research gap*

Literature shows that sustainability science and resilience theory have been studied independently (Derissen et al., 2011; Redman, 2014). In the same fashion, the existing modeling efforts do not explicitly link resilience aspects to sustainability issues. In reality, there are situations in which sustainability initiatives and practices can influence SC capacity in tackling unanticipated disruptions. For example, most sustainability practices push for increased efficiency in the use of resources and reduced protective redundancies (i.e., fewer stock points and storage areas along the SC). Whilst such practices may be environmentally sound and economically prudent, they may inadvertently cause the SCs becoming more vulnerable to disruptions given the limited availability of safety stock inventory to cope with supply and demand variations (Reyes Levalle and Nof, 2015). Likewise, sustainable sourcing practices imply the need to purchase from and outsource to more sustainable suppliers only. Yet, working with a handful of better performing suppliers comes with an unintended inability to switch between suppliers when facing a supply crisis.

It is therefore unrealistic to perform a SC sustainability analysis without touching upon the question of how sustainability initiatives can affect the system resilience. Considering sustainability tradeoff as a steady-state equilibrium is an unrealistic assumption given the increasing frequency of disruptions facing today's organizations and their inevitable consequences on the sustainability performance of the SCs. We see this as major research gap and call for management approaches and decision-support tools and techniques for integrating SC sustainability and resilience practices. We also realize that such intricate exercises require dynamic and multifactorial sustainability analysis for developing resiliently sustainable SCs whose sustainability remain less affected when disruptions arise.

Recognizing this gap in the existing literature, our aim in this article is to develop a simple optimization model that can be used to perform a dynamic sustainability tradeoff analysis and design a resiliently sustainable SC. A multi-objective optimization model is presented that utilizes a sustainability performance scoring approach to quantify the environmental and social impacts of the SC. A stochastic fuzzy goal programming approach is developed to find tradeoff solutions to the proposed multi-objective problem. The application of the proposed model and methodology is investigated in an empirical case study of a sportswear manufacturing company. Our analysis and discussions focus on comparing the numerical results obtained from static and dynamic sustainability tradeoff analyses.

## 3. Mathematical modeling

### *3.1. Problem statement*

The problem, at a glance, is to design a SC comprising suppliers, factories and distribution centers (DCs) in a way to minimize cost and maximize the environmental and social performance, whilst ensuring that the designed SC is resilient to supplier disruptions. We study a SC comprised of geographically dispersed factories, each served by a number of raw material suppliers with limited supply capacities. Items produced in factories are distributed to market zones through intermediate DCs. Factories and DCs can be established in different capacities (e.g., small, medium and large sizes) which would make a difference in fixed and variable costs of production and storage. Multiple transport modes, with different per unit shipping costs, may be available for the transportation of items between SC nodes.

The cost of raw material and the associated sustainability performance scores may vary from one supplier to another. The sustainability performance of a supplier is represented by an environmental performance score (EPS) and a social performance score (SPS). Determining EPSs and SPSs requires a set of assessment criteria upon which a supplier can be assessed. The assessment criteria for EPSs can be obtained from the comprehensive performance metrics adopted by the established environmental impact assessment methods such as IMPACT 2002+ (Jolliet et al., 2003), Eco-indicator 99 (Goedkoop et al., 2009) and CML2001 (Guinèe et al., 2001). Similarly, the metrics defined by social performance standards and guidelines of SA8000 (SAI, 2008), GRI (GRI, 2011) and GSLCAP (Benoıt and Mazijn, 2009) can be used to set the criteria for determining SPSs. Such assessment criteria may however need to be further refined to focus on those quantifiable items that (1) are directly related to strategic SC design decisions and (2) comply with the characteristics of the specific case situation (see the example presented in Section 4).

Once the environmental and social performance criteria are established, the suppliers' performance will be assessed against each criterion. A score, on a scale of 1–10, is assigned to the performance against each criterion (with 10 being the best practice). These scores are then averaged to generate aggregate averaged scores for EPS and SPS. A more precise approach to determine the aggregate scores would be to assign a weight to each criterion based upon its degree of importance to the focal company, and use a weighted averaging method to develop "aggregate weighted EPS and SPS scores".

The raw material supply is subject to disruption. A set of scenarios are developed to represent situations in which one or more suppliers are affected by disruptions. The model and methodology presented in this section aim to determine the sourcing strategies (i.e., the quantities to purchase from each supplier) and network design decisions (i.e., the location and capacity of factories and DCs) that minimize the overall SC cost and maximize its sustainability performance in both business-as-usual and supply disruption situations. The primary goal of our case study investigation in Section 4 is to utilize this model to perform a dynamic sustainability analysis for developing a resiliently sustainable SC.

### 3.2. A multi-objective mathematical model

A set of indices, parameters and decision variables are used for mathematical modeling of this problem.

*Sets and indices*

| | |
|---|---|
| $R$ | Set of raw material types, indexed by $r$ |
| $I$ | Set of product types/families, indexed by $i$ |
| $N$ | Set of suppliers, indexed by $n$ |
| $M$ | Set of candidate locations for factories, indexed by $m$ |
| $W$ | Set of candidate locations for DCs, indexed by $w$ |
| $J$ | Set of market zones, indexed by $j$ |
| $U$ | Set of capacity levels in factories, indexed by $u$ |
| $V$ | Set of capacity levels in DC, indexed by $v$ |
| $K$ | Set of transport modes for the shipment of products from factories to DCs, indexed by $k$ |
| $L$ | Set of transport modes for the shipment of products from DCs to market zones, indexed by $l$ |
| $S$ | Set of disruption scenarios, indexed by $s$ |

*Input parameters*

| | |
|---|---|
| $a_n^s$ | Equal to 1 if supplier $n$ is disrupted in scenario $s$; 0, otherwise |
| $a'_{rnm}$ | Equal to 1 if supplier $n$ is available to supply raw material $r$ for factory $m$; 0, otherwise |
| $h_{ri}$ | Amount of raw material $r$ required for production of a unit of product $i$ (kg) |
| $c_{rn}$ | Supply capacity of raw material $r$ by supplier $n$ (kg) |
| $d_{ij}^s$ | Forecasted demand for product $i$ in market zone $j$ in scenario $s$ (unit) |
| $f_n$ | Fixed cost of evaluating and selecting supplier $n$ ($) |
| $f'_{um}$ | Fixed cost of establishing a factory with capacity level $u$ at location $m$ ($) |
| $f''_{vw}$ | Fixed cost of establishing a DC with capacity level $v$ at location $w$ ($) |
| $t_{rnm}$ | Variable cost of purchasing raw material $r$ from supplier $n$ to factory $m$ ($/unit) |
| $g_{im}$ | Variable cost of manufacturing a unit of product $i$ in factory $m$ ($/unit) |
| $g'^s_{ij}$ | Unit cost of lost sales for product $i$ at market zone $j$ under scenario $s$ ($/unit) |
| $h'_{im}$ | Processing time to produce a unit of product $i$ in factory $m$ (h) |
| $c'_{um}$ | Production capacity of a factory with capacity level $u$ at location $m$ (h) |
| $t'_{imwk}$ | Unit cost of transportation for the shipment of product $i$ from factory $m$ to DC $w$ using transport mode $k$ ($/unit) |
| $t''_{iwjl}$ | Unit cost of transportation for the shipment of product $i$ from DC $w$ to market zone $j$ using transport mode $l$ ($/unit) |
| $h''_i$ | Volume of a unit of product $i$ ($m^3$) |
| $c''_{vw}$ | Storage capacity of a DC with capacity level $v$ at location $w$ ($m^3$) |
| $e_{rmn}$ | EPS of supplier $n$ for the supply of raw material $r$ to factory $m$ (score) |
| $e'_{rmn}$ | SPS of supplier $n$ for the supply of raw material $r$ to factory $m$ (score) |
| $q^s$ | Probability of occurrence of scenario $s$ |

*Decision variables*

| | |
|---|---|
| $X_n$ | A binary variable, equal to 1 if supplier $n$ is selected; 0, otherwise |
| $X'_{um}$ | A binary variable, equal to 1 if a factory with capacity level $u$ is established at location $m$; 0, otherwise |
| $X''_{vw}$ | A binary variable, equal to 1 if a DC with capacity level $v$ is established at location $w$; 0, otherwise |
| $Q_{rnm}^s$ | Quantity of raw material $r$ shipped from supplier $n$ to factory $m$ under scenario $s$ |
| $P_{im}^s$ | Quantity of product $i$ produced in factory $m$ under scenario $s$ |
| $Y_{imwk}^s$ | Quantity of product $i$ shipped from factory $m$ to DC $w$ using transport mode $k$ under scenario $s$ |
| $Y'^s_{iwjl}$ | Quantity of product $i$ shipped from DC $w$ to market zone $j$ using transport mode $l$ under scenario $s$ |
| $Y''^s_{ij}$ | Quantity of lost sales for product $i$ at market zone $j$ under scenario $s$ |

We use a two-stage programming approach (see Birge and Louveaux (2011)) to formulate the problem under investigation. For this, decision variables are split into two categories: scenario-independent variables, including $X_n$, $X'_{um}$ and $X''_{vw}$, and scenario-dependent variables, including all decision variables except for $X_n$, $X'_{um}$ and $X''_{vw}$. Determining the values of scenario-independent variables is not reliant on the scenario realization. These are determined at stage 1. Decisions on scenario-dependent variables are then made in stage 2 once a disruption scenario is realized.

The proposed model has three primary objective functions corresponding to the economic, environmental and social performance of the SC. Objective function (1), formulated in Eq. (1), represents the cost performance of the SC under scenario $s$. The components of Eq. (1) include the cost of supplier evaluation and selection, cost of establishing factories, cost of establishing DCs, cost of raw material, production cost, transportation cost from factories to DCs, transportation cost from DCs to market zones, and cost of lost sales. The economic goal is to minimize the value of objective function (1).

$$\begin{aligned}\text{Objective function 1} = &\sum_{n\in N} f_n X_n + \sum_{u\in U}\sum_{m\in M} f'_{um}X'_{um} + \sum_{v\in V}\sum_{w\in W} f''_{vw}X''_{vw} + \sum_{r\in R}\sum_{n\in N}\sum_{m\in M} t_{rnm}Q^s_{rnm} + \sum_{i\in I}\sum_{m\in M} g_{im}P^s_{im} \\ &+ \sum_{i\in I}\sum_{m\in M}\sum_{w\in W}\sum_{k\in K} t'_{imwk}Y^s_{imwk} + \sum_{i\in I}\sum_{w\in W}\sum_{j\in J}\sum_{l\in L} t''_{iwjv}Y'^s_{iwjl} + \sum_{i\in I}\sum_{j\in J} g'^s_{ij}Y''^s_{ij}\end{aligned} \tag{1}$$

Objective function (2), presented in Eq. (2), calculates the aggregate weighted environmental scores of all suppliers under scenario $s$. The environmental goal of the model is to maximize the value of objective function (2).

$$\text{Objective function 2} = \sum_{r\in R}\sum_{n\in N}\sum_{m\in M} e_{rmn}Q^s_{rnm} \tag{2}$$

Objective function (3) is formulated in Eq. (3) and computes the aggregate weighted social scores of all suppliers under scenario $s$. The social goal of the model is to maximize the value of objective function (3).

$$\text{Objective function 3} = \sum_{r\in R}\sum_{n\in N}\sum_{m\in M} e'_{rmn}Q^s_{rnm} \tag{3}$$

It is noteworthy that developing a more generic mathematical model would necessitate the incorporation of environmental and social performance scores related to manufacturing and storage of products into Eqs. (2) and (3). Given the clear focus of our analysis and investigation on supplier performance management issues, the formulations of objective functions 2 and 3 were reduced to only include the suppliers' sustainability performance, leaving the sustainability of manufacturing plants and DCs outside the area of our study focus.

The proposed model is subject to the following constraints.

$$\sum_{u\in U} X'_{um} \leqslant 1 \quad \forall m \in M \tag{4}$$

$$\sum_{v\in V} X''_{vw} \leqslant 1 \quad \forall w \in W \tag{5}$$

$$Q^s_{rnm} \leqslant a'_{rnm}X_n \quad \forall r\in R, \forall n\in N, \forall m\in M, \forall s\in S \tag{6}$$

$$\sum_{n\in N} Q^s_{rnm} = \sum_{i\in I} h_{ri}P^s_{im} \quad \forall r\in R, \forall m\in M, \forall s\in S \tag{7}$$

$$P^s_{im} = \sum_{w\in W}\sum_{k\in K} Y^s_{imwk} \quad \forall i\in I, \forall m\in M, \forall s\in S \tag{8}$$

$$\sum_{m\in M}\sum_{k\in K} Y^s_{imwk} = \sum_{j\in J}\sum_{l\in L} Y'^s_{iwjl} \quad \forall i\in I, \forall w\in W, \forall s\in S \tag{9}$$

$$\sum_{w\in W}\sum_{l\in L} Y'^s_{iwjl} + Y''^s_{ij} = d^s_{ij} \quad \forall i\in I, \forall j\in J, \forall s\in S \tag{10}$$

$$\sum_{m\in M} Q^s_{rnm} \leqslant (1 - a^s_n)c_{rn}X_n \quad \forall r\in R, \forall n\in N, \forall s\in S \tag{11}$$

$$\sum_{i\in I} h'_{im}P^s_{im} \leqslant \sum_{u\in U} c'_{um}X'_{um} \quad \forall m\in M, \forall s\in S \tag{12}$$

$$\sum_{i\in I}\sum_{m\in M}\sum_{k\in K} h''_{it}Y^s_{imwk} \leqslant \sum_{v\in V} c''_{vw}X''_{vw} \quad \forall w\in W, \forall s\in S \tag{13}$$

$$X_n \in \{0,1\} \quad \forall n\in N \tag{14}$$

$$X'_{um} \in \{0,1\} \quad \forall u\in U, \forall m\in M \tag{15}$$

$$X''_{vw} \in \{0,1\} \quad \forall v\in V, \forall w\in W \tag{16}$$

$$Q^s_{rnm} \geqslant 0 \quad \forall r\in R, \forall n\in N, \forall m\in M, \forall s\in S \tag{17}$$

$$P^s_{im} \geqslant 0 \quad \forall i\in I, \forall m\in M, \forall s\in S \tag{18}$$

$$Y^s_{imwk} \geqslant 0 \quad \forall i\in I, \forall m\in M, \forall w\in W, \forall k\in K, \forall s\in S \tag{19}$$

$$Y'^{s}_{iwjl} \geqslant 0 \quad \forall i \in I, \forall w \in W, \forall j \in J, \forall l \in L, \forall s \in S \tag{20}$$

$$Y''^{s}_{ij} \geqslant 0 \quad \forall i \in I, \forall j \in J, \forall s \in S \tag{21}$$

Constraint (4) ensures that no more than one factory can be established in a candidate location. Constraint (5) applies the same for establishing DCs. Constraint (6) ensures that raw materials are supplied to a factory only by suppliers available to that factory. Constraint (7) guarantees the fulfillment of raw material requirement in factories. Constraints (8)–(10) represent the flow balance constraints in factories, DCs and market locations, respectively. Constraints (11)–(13) enforce the capacity limitations of the suppliers, factories and DCs, respectively. Constraints (14)–(20) define the domains of the decisions variables.

### 3.3. A stochastic fuzzy goal programming approach

In multi-objective problems with conflicting objectives, there is no one unique solution that can optimize all the objectives at once. In most cases, an objective function is improved at the cost of compromising at least one other objective. Multi-objective solution approaches seek a tradeoff solution or a set of tradeoff solutions (the so-called Pareto optimal solutions) that simultaneously satisfy multiple, usually conflicting, objectives.

Numerous approaches have been developed and applied to solve multi-objective mathematical problems. Arguably, weighted sum methods and goal programming are amongst the simplest and most popular techniques. Weighted sum methods aim to convert multiple objectives into a single objective equivalent by assigning a weight to each objective function corresponding to its importance (Arntzen et al., 1995). A weight will be a normalization constant if objective values have different units/dimensions. In goal programing, instead of minimizing or maximizing the objective functions, their deviations from goals, also called aspiration levels, are minimized (Aouni and Kettani, 2001). A weighted goal programming approach assigns weighting coefficients (or normalization constants if different dimensions) to the deviation values to generate a unified objective function.

The primary difficulty with these methods is determining the weight of each objective function. A fuzzy programming approach (Zimmermann, 1978) aims to tackle this by expressing the relative importance of each goal (Aköz and Petrovic, 2007; Chen and Tsai, 2001; Narasimhan, 1980; Tiwari et al., 1987). Fuzzy goal programming has been a popular approach to solving multi-objective operations, logistics and SC management problems and its applications have been studied in a breadth of problems ranging from aggregate production planning (Jamalnia and Soukhakian, 2009; Wang and Liang, 2004) to supplier evaluation and selection (Amid et al., 2006; Chen et al., 2006; Kumar et al., 2004), SC network design (Özceylan and Paksoy, 2012; Selim and Ozkarahan, 2008) and SC planning (Liang, 2007; Selim et al., 2008; Torabi and Hassini, 2008). One drawback of a fuzzy goal programming approach may be that it cannot guarantee Pareto-optimal solutions to nonconvex problems.

For the multi-objective model encountered in this article, we propose a stochastic fuzzy goal programming approach in which the expected value of the objective functions are obtained for a set of possible disaster scenarios (the stochastic programming component) and then the weights of objective functions are expressed using a fuzzy linguistic approach (the fuzzy programming component). In other words, the *stochastic* and *fuzzy* aspects are combined to tackle the co-occurrence of uncertainty in disruption likelihood and imprecise weight of objective functions.

The first step is to develop a set of possible disruption scenarios to represent situations where one or more suppliers are affected by disruptions. Scenario 1 is defined as "business-as-usual" where no disruption occurs. Our initial test experiments showed that the fuzzy-based approach presented in this article is able to effectively deal with large number of scenarios of over 1000. So, considering all potential disruption scenarios is not impossible. However, various scenario reduction methods can be adopted to deal with situations when the number of possible disruption scenarios can be excessively large – the so-called "curse of dimensionality" (see for example Heitsch and Romisch (2003, 2007), Dupačová et al. (2003) and Growe-Kuska and Romisch (2005)).

Next is to formulate the economic, environmental and social goals of the SC for both business-as-usual ($s = 1$) and supply disruption situations. Using Eqs. (1)–(3) as the three primary objective functions, Eqs. (22)–(24) present the economic, environmental and social sustainability goals for the business-as-usual and Eqs. (25)–(27) present these goals for supply disruption situations ($s > 1$).

Goal 1 (minimizing the SC cost in the business-as-usual):

$$\begin{aligned}\text{Minimize } G_1 = &\sum_{n\in N} f_n X_n + \sum_{u\in U}\sum_{m\in M} f'_{um} X'_{um} + \sum_{v\in V}\sum_{w\in W} f''_{vw} X''_{vw} + \sum_{r\in R}\sum_{n\in N}\sum_{m\in M} t_{rnm} Q^1_{rnm} + \sum_{i\in I}\sum_{m\in M} g_{im} P^1_{im} \\ &+ \sum_{i\in I}\sum_{m\in M}\sum_{w\in W}\sum_{k\in K} t'_{imwk} Y^1_{imwk} + \sum_{i\in I}\sum_{w\in W}\sum_{j\in J}\sum_{l\in L} t''_{iwjv} Y'^1_{iwjl} + \sum_{i\in I}\sum_{j\in J} g'^s_{ij} Y''^1_{ij}\end{aligned} \tag{22}$$

Goal 2 (maximizing the aggregate weighted EPS in the business-as-usual):

$$\text{Maximize } G_2 = \sum_{r\in R}\sum_{n\in N}\sum_{m\in M} e_{rmn} Q^1_{rnm} \tag{23}$$

Goal 3 (maximizing the aggregate weighted SPS in the business-as-usual):

$$\text{Maximize } G_3 = \sum_{r\in R}\sum_{n\in N}\sum_{m\in M} e'_{rmn} Q^1_{rnm} \tag{24}$$

Goal 4 (minimizing the expected SC cost in supply disruptions):

$$\begin{aligned}\text{Minimize } G_4 = &\sum_{n\in N} f_n X_n + \sum_{u\in U}\sum_{m\in M} f'_{um} X'_{um} + \sum_{v\in V}\sum_{w\in W} f''_{vw} X''_{vw} \\ &+ \sum_{s\in S-\{1\}} \frac{q^s}{\left(\sum_{s\in S-\{1\}} q^s\right)} \left( \begin{array}{l} \sum_{r\in R}\sum_{n\in N}\sum_{m\in M} t_{rnm} Q^s_{rnm} + \sum_{i\in I}\sum_{m\in M} g_{im} P^s_{im} + \sum_{i\in I}\sum_{m\in M}\sum_{w\in W}\sum_{k\in K} t'_{imwk} Y^s_{imwk} \\ + \sum_{i\in I}\sum_{w\in W}\sum_{j\in J}\sum_{l\in L} t''_{iwjv} Y'^s_{iwjl} + \sum_{i\in I}\sum_{j\in J} g'_{ijs} Y''^s_{ij} \end{array} \right)\end{aligned} \tag{25}$$

Goal 5 (maximizing the expected aggregate weighted EPS in supply disruptions):

$$\text{Maximize } G_5 = \sum_{r\in R}\sum_{n\in N}\sum_{m\in M}\sum_{s\in S-\{1\}} \frac{q^s}{\left(\sum_{s\in S-\{1\}} q^s\right)} e_{rmn} Q^s_{rnm} \tag{26}$$

Goal 6 (maximizing the expected aggregate weighted SPS in supply disruptions):

$$\text{Maximize } G_6 = \sum_{r\in R}\sum_{n\in N}\sum_{m\in M}\sum_{s\in S-\{1\}} \frac{q^s}{\left(\sum_{s\in S-\{1\}} q^s\right)} e'_{rmn} Q^s_{rnm} \tag{27}$$

Fuzzy programming is used to express the relative importance of each goal. Eqs. (28)–(33) formulate the degree of satisfaction of each goal (Aköz and Petrovic, 2007; Chen and Tsai, 2001; Narasimhan, 1980; Tiwari et al., 1987).

$$\text{Degree of satisfaction of goal 1} = \mu_1 = \frac{\beta_1 - G_1}{\beta_1 - \alpha_1} \tag{28}$$

$$\text{Degree of satisfaction of goal 2} = \mu_2 = \frac{G_2 - \beta_2}{\alpha_2 - \beta_2} \tag{29}$$

$$\text{Degree of satisfaction of goal 3} = \mu_3 = \frac{G_3 - \beta_3}{\alpha_3 - \beta_3} \tag{30}$$

$$\text{Degree of satisfaction of goal 4} = \mu_4 = \frac{\beta_4 - O_4}{\beta_4 - \alpha_4} \tag{31}$$

$$\text{Degree of satisfaction of goal 5} = \mu_5 = \frac{G_5 - \beta_5}{\alpha_5 - \gamma_5} \tag{32}$$

$$\text{Degree of satisfaction of goal 6} = \mu_6 = \frac{G_6 - \beta_6}{\alpha_6 - \beta_6} \tag{33}$$

where $\alpha_1$–$\alpha_6$ denote the aspiration levels of the goals 1–6, respectively. $\beta_1$ and $\beta_4$ represent the upper tolerance limits for the total SC cost in business-as-usual (goal 1) and supply disruptions (goal 4) situations, respectively. $\beta_2$ and $\beta_5$ denote the lower tolerance limits for the aggregate EPS in business-as-usual (goal 2) and supply disruption (goal 5) situations, respectively. Likewise, $\beta_3$ and $\beta_6$ indicate the lower tolerance limits for the aggregate SPS in business-as-usual (goal 3) and supply disruption (goal 6) situations, respectively.

Linguistic terms are used to express the comparative importance of each goal. The linguistic terms include 'significantly more important', 'moderately more important', 'slightly more important', and 'equally important'. For example goal 1 can be significantly more important than goal 2, and goal 2 can be equally important to goal 3. To simplify the notations, let us set $\widetilde{R}_0$, $\widetilde{R}_1$, $\widetilde{R}_2$, and $\widetilde{R}_3$ denote the relations 'equally important', 'slightly more important', 'moderately more important', and 'significantly more important', respectively. Also, let $\widetilde{R}(z,z')$ denote the importance relationship between the two goals $z$ and $z'$ (i.e., the importance relationship between $G_z$ and $G_{z'}$). For example, $\widetilde{R}(1,3) = \widetilde{R}_2$ implies that goal 1 ($G_1$) is moderately more important than goal 3 ($G_3$).

Using the approach introduced by Aköz and Petrovic (2007), the proposed stochastic fuzzy goal programming model can be formulated as:

$$\text{maximize } \lambda\left(\sum_{z=1}^{6}\mu_z\right) + (1-\lambda)\left(\sum_{z=1}^{6}\sum_{z'=1}^{6}\mu_{\widetilde{R}(z,z')}\right) \tag{34}$$

The proposed model is subject to:
Constraints (4)–(20)
Constraints (28)–(33)

$$\mu_z \leqslant 1 \quad z = 1,2,\ldots,6 \tag{35}$$

$$\mu_z - \mu_{z'} + 1 \geqslant \mu_{\widetilde{R}_1(z,z')} \quad \text{for all and } \widetilde{R}(z,z') = \widetilde{R}_1 \tag{36}$$

$$\frac{\mu_z - \mu_{z'} + 1}{2} \geqslant \mu_{\widetilde{R}_2(z,z')} \quad \text{for all } \widetilde{R}(z,z') = \widetilde{R}_2 \tag{37}$$

$$\mu_z - \mu_{z'} \geqslant \mu_{\widetilde{R}_3(z,z')} \quad \text{for all } \widetilde{R}(z,z') = \widetilde{R}_3 \tag{38}$$

$$\mu_{\widetilde{R}(z,z')} \leqslant 1 \quad \text{for all } \widetilde{R}(z,z') \tag{39}$$

$$\mu_z \geqslant 0 \quad z = 1, 2, \ldots, 6 \tag{40}$$

$$\mu_{\widetilde{R}(z,z')} \geqslant 0 \quad \text{for all } \widetilde{R}(z,z') \tag{41}$$

In this model, the priority structure (i.e., the importance relationship between the goals) may be only satisfied to a certain degree. $\mu_{\widetilde{R}(z,z')}$ is defined as a decision variable that represents the degree of satisfaction of the importance relationship $\widetilde{R}(z,z')$. Changing parameter $\lambda$ within the interval $[0,1]$ (i.e., $0 \leqslant \lambda \leqslant 1$) generates different solutions. As $\lambda$ decreases, the relative priority relations receive greater weights and solutions that better satisfy these relations will be sought. A suitable value for $\lambda$ needs to be determined by a decision maker through a parameter adjustment exercise. More details about the fuzzy goal programming approach can be found in Aköz and Petrovic (2007).

## 4. Case study and discussions

### 4.1. The case environment and decision scenarios

ACO is a multinational corporation involved in the production and distribution of sportswear clothing. ACO is headquartered in Australia and has factories in four Asian countries – China (Quanzhou), Vietnam (Ho Chi Minh), Cambodia (Phnom Penh) and Bangladesh (Dhaka). Synthetic fabric is the primary raw material used in all product types. The required fabrics at each factory are sourced from a number of local suppliers. The factories in China and Bangladesh are each served by six raw material suppliers and factories in Vietnam and Cambodia have five local suppliers each. Synthetic fibers are produced at supplier sites by forcing liquids through tiny holes in a metal plate, called a spinneret, and allowing them to harden. The use of different liquids and spinnerets produce various types of fibers such as polyester, nylon, acrylic and rayon. The fiber production process is energy intensive and involves substantial water use.

ACO manufactures four families of products, including tops, pants, shorts, and jackets. Production processes are identical in all factories and include design, cutting, sewing, assembly, and packaging. In a SC reconfiguration problem, which is the scope of this case study analysis, a factory can be resized to match the network requirement. The capacity of a factory can be increased at a fixed facility expansion cost. Three capacity levels are considered for a factory corresponding to the required production outputs.

Products are shipped from factories to wholesalers (market zones) in the five Australian states of New South Wales (NSW), Victoria (VIC), Queensland (QLD), South Australia (SA) and Western Australia (WA) through three DCs in WA (Perth), SA (Adelaide) and NSW (Sydney). A DC can be leased in three sizes: large, medium, and small. The leases are signed for strategic periods, typically longer than two years, to allow for the long-term installation of shelves and material handling systems. Sea transport is the only option for the shipment of products from Asian factories to Australian DCs (although, samples for design purposes are usually shipped via air transport). The inbound transportation for the shipment of items from DCs to wholesalers can be via rail, road and sea transport modes. The schematic view of the SC for ACO is shown in Fig. 1.

A systematic mechanism was employed in 2014 for assessment and scoring the environmental and social performance of each supplier (determining aggregate EPS and SPS values). A panel of industry experts, comprised of three individuals from two Asian and one Australian sustainability consultancy firms with specialized expertise in the apparel industry, was formed to assist with this process. Due to the energy and water intensive nature of synthetic fabric production, "alternative energy sources" and "water consumption" were identified by the panel of experts as the primary performance metrics for determining EPSs. The supplier's "GHG emissions performance" was also added as a third criterion in response to the global emissions reduction trends and regulatory mandates. The three criteria were weighted based on their importance as 40–40–20, corresponding to available energy sources, water consumption and GHG emissions generation, respectively.

For the social assessment criteria, the performance metrics defined in the reporting guidelines of GRI (GRI, 2011) were used to set the foundation. The criteria were further refined by the panel of experts to those concerning the strategic SC decisions for synthetic product manufacturing in Asia–Pacific region. A similar approach has been undertaken in the past by other researchers (Boukherroub et al., 2015; Pishvaee and Razmi, 2012; Pishvaee et al., 2012; You et al., 2012). The criteria were organized in four equally weighted categories of labor practices and decent work (including fair wages, working condition, occupational health and safety, and training and education), human rights (including child labor, forced labor, and discrimination incidents), society (including local community investment and public policy involvement), and product responsibility (including product labeling and customer privacy).

Once the environmental and social performance criteria were established, site visits and direct investigations were completed by the panel of experts to assess the suppliers' performance against each criterion. All observations related to the supplier auditing process were documented. The performance of each supplier against each criterion received an assessment score on a scale of 1–10, with 10 being the best practice. With these assessment scores, the aggregate weighted EPS and SPS values for each supplier could then be generated using a weighted averaging method (i.e., 40–40–20 weighted criteria

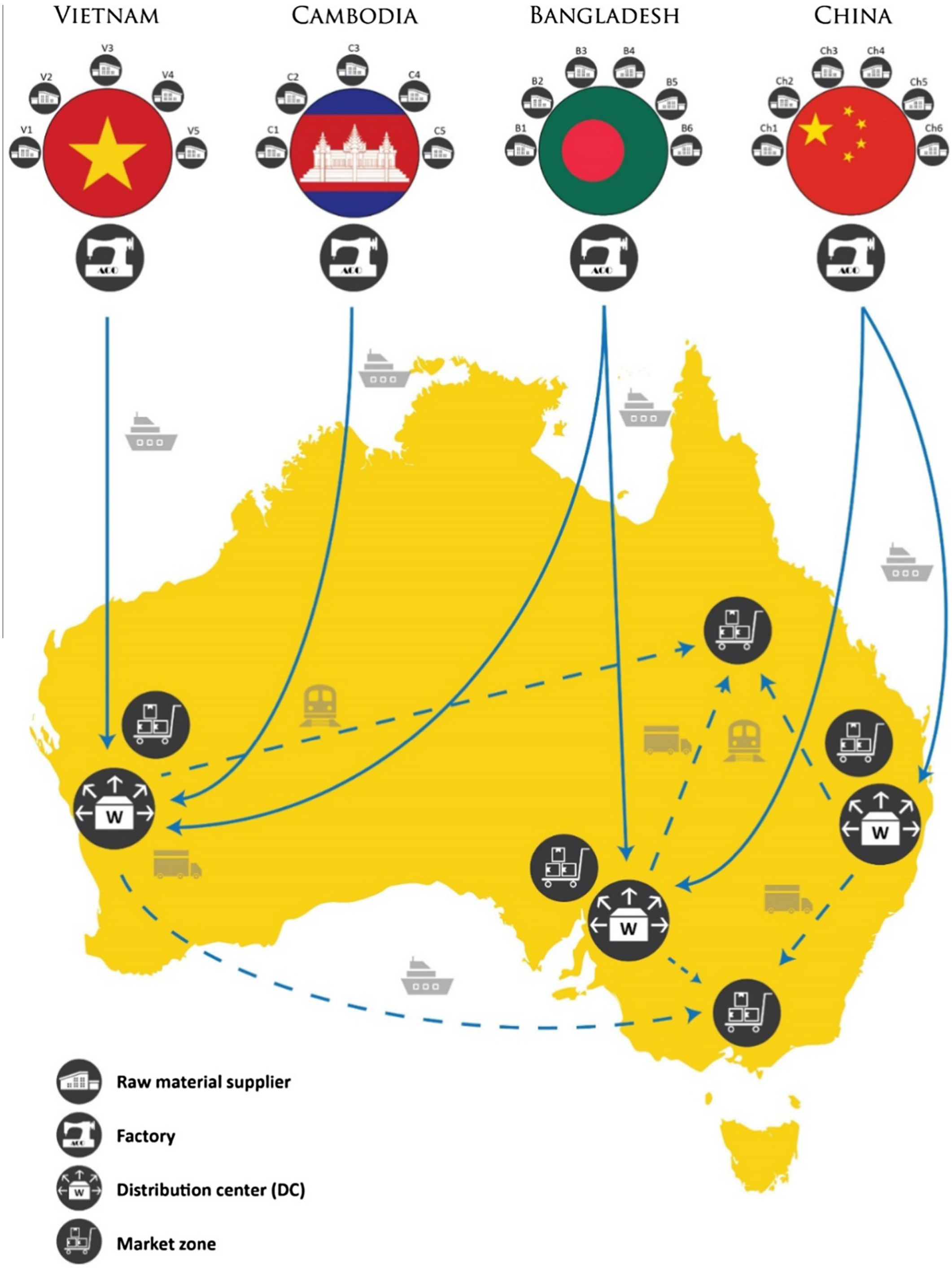


**Fig. 1.** The SC configuration in ACO.

for EPS calculation and equally weighted criteria for SPS calculation, as discussed above) for the supply of a certain raw material to factory. For the purpose of our analyses in this article, suppliers of each factory are numbered on the basis of their EPS and SPS values. For example, for the factory in China, Ch6 (supplier #6) possess the highest EPS and SPS, while Ch1 (supplier #1) shows the poorest sustainability performance amongst the six.

Our experiments and discussion in this section focus on the suppliers' sustainability performance and its impact on the overall SC resilience. The reason for this study scope is the paramount importance of the sustainability performance and reliability of synthetic fiber suppliers in garment manufacturing (which is also the case in many other industries). To help

**Table 1**
Characteristics of the supply disruption scenarios.

| Disruption scenario | Affected supplier(s) |
|---|---|
| *Business-as-usual scenario* | |
| Scenario 1 ($s1$) | – |
| *Supply disruption scenario* | |
| Scenario 2–7 ($s2$–$s7$) | Ch1–Ch6 affected, respectively |
| Scenario 8–12 ($s8$–$s12$) | V1–5 affected, respectively |
| Scenario 13–17 ($s13$–$s17$) | C1–C5 affected, respectively |
| Scenario 18–23 ($s18$–$s23$) | B1-B6 affected, respectively |
| Scenario 24 ($s1$) | Ch1–Ch6 simultaneously affected |
| Scenario 25 ($s1$) | V1–5 simultaneously affected |
| Scenario 26 ($s1$) | C1–C5 simultaneously affected |
| Scenario 27 ($s1$) | B1–B6 simultaneously affected |

our analyses and discussions, a set of disruption scenarios are defined so that the SC sustainability tradeoff can be investigated in both business-as-usual and supply disruption situations. The characteristics of the disruption scenarios are shown in Table 1.

Scenario 1 represents the SC status in business-as-usual when no supply disruption occurs. Scenarios 2–23 represent situations when one supplier is affected by an unforeseen disruption (i.e., one supplier is affected at a time). Scenarios 24–27 represent situations when all suppliers of a factory in one region are affected simultaneously (i.e., no production occur in that region/country). Obviously, additional scenarios can be developed comprising other possible combinations of affected suppliers. Here, we focus our analysis on a reasonable number of scenarios identified by the panel of experts as the most likely/plausible to occur. Scenario reduction methods can be used to deal with situations when the number of possible disruption scenarios can be excessively large (Dupačová et al., 2003; Growe-Kuska and Romisch, 2005; Heitsch and Romisch, 2003, 2007).

The model presented in Section 3 was coded in GAMS 24.1. The following sections present a static sustainability tradeoff analysis (in business-as-usual) and a dynamic sustainability tradeoff analysis (under potential supply disruptions) for the proposed case company and its parametric data. All experiments are completed on a laptop with Intel Core i7-4702HQ CPU, 2.2 GHz with 16 GB of RAM. The runtimes are not reported since they were shown to be negligible (only a few seconds in most runs).

### *4.2. Static sustainability tradeoff analysis*

This section presents a basic SC sustainability analysis that aims to explore the tradeoffs between the economic and non-economic goals in a business-as-usual environment (i.e., disregarding the likelihood of a disruption occurrence). The non-economic sustainability goals include both environmental and social goals. In aid of a more focused discussion, we assume equal importance of the environmental and social goals and focus our analyses on evaluating the tradeoff between the economic goal (minimizing the SC cost) and the non-economic goals (minimizing the equally-weighted aggregate EPS and SPS values).

Fig. 2 shows the initial results of the static sustainability analysis (using the goals 1–3 in Eqs. (21)–(23)), for various degrees of the relative importance of the economic goal to the non-economic goals. The figure illustrates how the economic, environmental and social performance of the SC varies with changes in the relative importance of the economic goal. Not surprisingly, the greater is the relative importance of the economic goal, the lower is the SC cost and average aggregate EPS/SPS values. The SC cost in this case increases nonlinearly, by as much as 17%, while the economic and environmental performance of the SC (measured by the average weighted aggregate EPS and SPS values) rises relatively linearly as the relative importance of the economic goal diminishes. This observation can help a decision maker identify opportunities where greater enhancements in environmental and social performance can be achieved per dollar SC cost increase.

The relative importance of the economic goal to the non-economic goals has impacts on the sourcing decisions and subsequently on the overall configuration of the SC (i.e., location and capacity of factories and DCs). Tables 2 and 3 show the resulting sourcing and facility location/capacity decisions for each relative importance degree of the economic goal. Table 2 shows the level of involvement of each supplier. In all four situations, approximately half of the suppliers are utilized for raw material acquisition. There are suppliers that are selected under all configurations (V3–V4 and C4–C5) and those that are not selected under any (Ch1–Ch3 and C1). The level of a supplier involvement is obviously a function of its economic, environmental and social performance. Evidently, there is a tendency to select the more sustainable suppliers as the economic goal becomes less emphasized.

Table 3 shows variations in the location and capacity of SC facilities as changes occur in the relative importance of the economic goal. We see that decisions on a factory location and its production capacity are very much dependent on the related sourcing decisions. All configurations, regardless of the degree importance of economic goal, establish one medium and two small factories. Under no circumstances is a large factory opened. Factory m1 in China, the most sustainable in

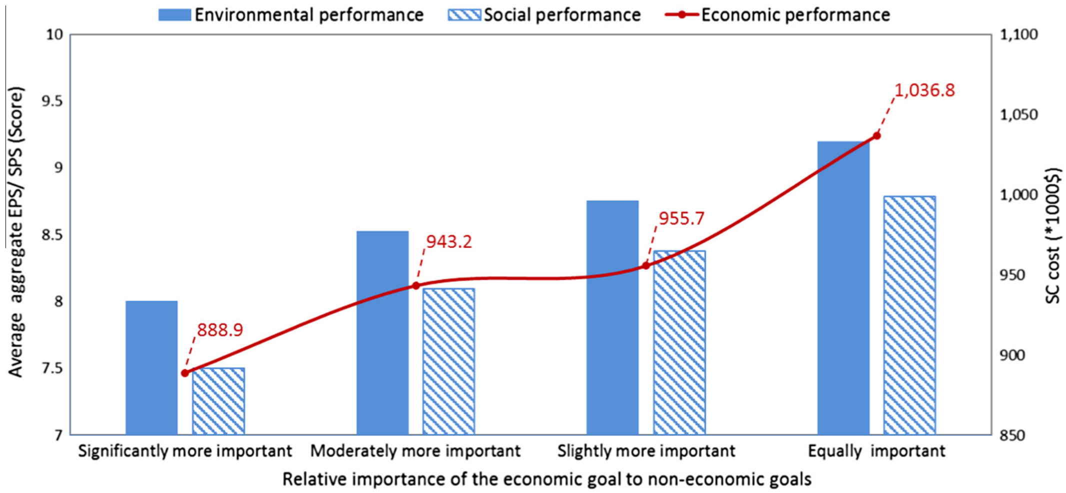


**Fig. 2.** Static analysis: SC performance when varying the relative importance of the economic goal.

**Table 2**
Static analysis: percentage raw material purchased from each supplier under different SC configurations.

| Supplier | Relative importance of the economic goal to the non-economic goals | | | |
|---|---|---|---|---|
| | Significantly more important | Moderately more important | Slightly more important | Equally important |
| Ch1 | | | | |
| Ch2 | | | | |
| Ch3 | | | | |
| Ch4 | | | | 1.7 |
| Ch5 | | | | 11.4 |
| Ch6 | | | | 22.2 |
| V1 | 6.1 | | 0.1 | 0.1 |
| V2 | 4.4 | | 6.6 | 3.3 |
| V3 | 5.0 | 4.4 | 7.4 | 7.4 |
| V4 | 4.8 | 8.7 | 8.8 | 8.8 |
| V5 | | 26.3 | 26.3 | 26.3 |
| C1 | | | | |
| C2 | | 0.6 | | |
| C3 | 14.5 | 8.8 | 0.4 | 0.2 |
| C4 | 26.2 | 11.4 | 11.4 | 6.3 |
| C5 | 1.7 | 22.1 | 22.1 | 12.3 |
| B1 | 9.4 | | | |
| B2 | 3.1 | | | |
| B3 | 1.4 | | | |
| B4 | | 2.2 | 2.2 | |
| B5 | 10.5 | 5.3 | 5.3 | |
| B6 | 12.9 | 10.2 | 9.4 | |

**Table 3**
Static analysis: changes in facility location/capacity decisions when varying relative importance of the economic goal.

| Relative importance of the economic goal | Factories | | | | DCs | | |
|---|---|---|---|---|---|---|---|
| | m1 | m2 | m3 | m4 | w1 | w2 | w3 |
| Significantly more important | | S[a] | S | M | S | L | S |
| Moderately more important | | S | M | S | S | M | M |
| Slightly more important | | M | S | S | S | M | M |
| Equally important | S | M | S | | S | M | M |

[a] Facility sizes L: Large, M: Medium, S: Small.

terms of its supplier performance, is the least preferred option (also confirmed by the sourcing decisions in Table 2) unless the economic and non-economic goals are equally weighted. The factory location results do not hold for locating DCs. All DCs

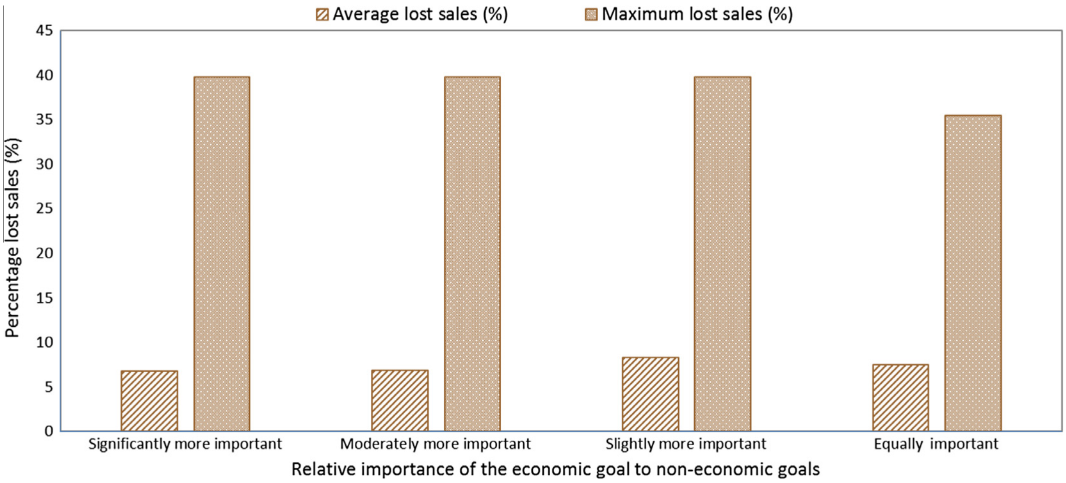


**Fig. 3.** Static analysis: absolute and percentage lost sales in the face of disruptions.

are operational in all configurations to satisfy the product distribution requirements, although w1 is always the smallest in size amongst the three.

Now, let us examine how a SC developed through the static sustainability analysis can cope with unforeseen supply disruptions. None of the four SC configurations resulting from the static sustainability analysis are able to fully satisfy the demands of all market in disruption scenarios as defined in Table 1. Fig. 3 shows the average and maximum percentage lost sales generated when supply disruptions occur (i.e., average percentage lost sales obtained from model run in 26 supply disruption scenarios outlined in Table 1). While the SC may experience as much as 40 percent demand under-fulfillment in a worst-case scenario, on average between 7% and 8% of the entire sales will be unsatisfied when disruptions occur. These rates are almost independent of the relative importance of the economic goal. Therefore, we conclude that none of the four SC configurations can provide a feasible solution to the problem in disruptions. With no feasible solution available, providing a complete and comparative tradeoff analysis for these four SC configurations is not possible.

One may suggest increasing the maximum production capacity of factories as an easy-fix strategy to shift production between factories when supply disruptions occur in one region. To examine this proposition, we performed a set of experiments in which we increased the production capacity of factories by 10 times. We found that not only did the strategy fail to find a feasible solution in disruptions, but also that the quantity of lost sales was increased by about two times. The reason for this is that fewer factories are opened to satisfy the same demand in the business-as-usual situation when higher-capacity factories are used. In this case, when a factory is affected by a supply disruption, there are fewer other factories and suppliers to compensate the supply shortage. Thus, increased production capacity cannot help improve demand fulfillment in the face of supply disruptions.

The above discussion reinforces why a static tradeoff analysis is simplistic and hence impractical in a real world context. The next section explains how a dynamic sustainability tradeoff analysis can help ACO design a SC that is able to provide efficient and effective solutions in both business-as-usual and disruption situations.

### 4.3. Dynamic sustainability tradeoff analysis

For the case study and its parametric data, we now complete a dynamic tradeoff analysis where sourcing and facility location decisions are made considering the SC performance in both business-as-usual and supply disruption situations (i.e., considering all six goals formulated in Section 3.3). Fig. 4 shows a summary of the numerical results. The figure is comprised of eight charts, as opposed to one chart in a static tradeoff analysis. The four charts in the left column illustrate the SC performance in business-as-usual; and the charts in the right column show the corresponding performance under potential supply disruptions. For each situation/column, the performance is recorded when varying "the importance degree of the economic goal" (shown in four rows) and "the importance degree of the business-as-usual performance" (shown within each chart). In other words, Fig. 4 illustrates the economic and non-economic performance of 16 SC configurations (four configurations in each chart) in business-as-usual and disruption situations (i.e., $16 * 2 = 32$ performance sets in total). Sourcing decisions and facility location/capacity decisions corresponding to each of the 16 SC configurations are presented in Tables 4 and 5 for the dynamic tradeoff analysis.

It should be noted that all results shown in the "SC performance in disruptions" column of Fig. 4 are obtained from solving Eqs. (24)–(26) which relate to the average SC performance in 26 supply disruption scenarios defined in Table 1. For example, "average expected SC cost" is calculated by averaging 26 expected cost values obtained from 26 supply disruption scenarios. Similarly, EPS and SPS values are obtained from averaging the weighted aggregate EPS and SPS values in 26 supply disruption

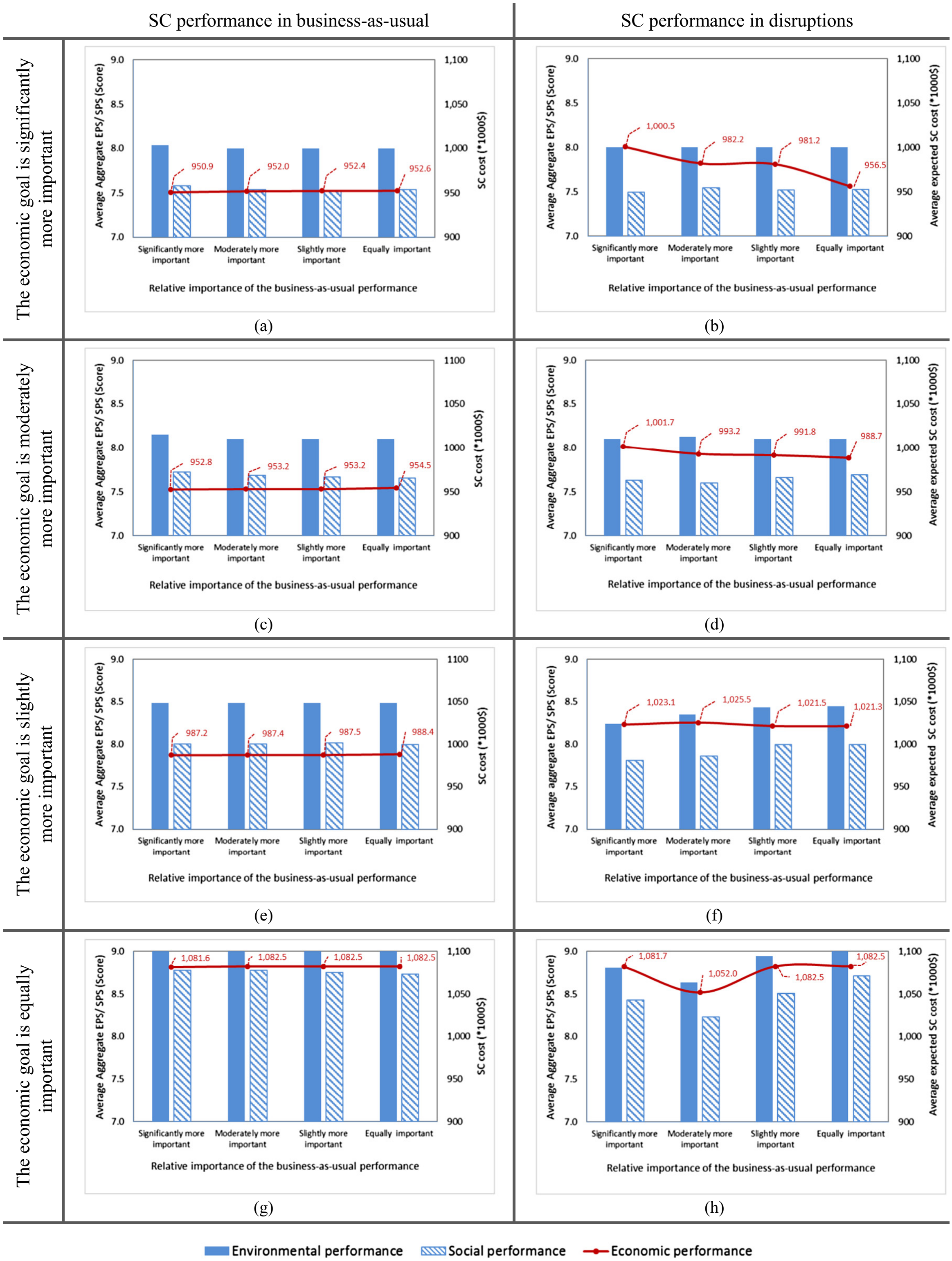


**Fig. 4.** Dynamic analysis: SC performance in business-as-usual and disruption situations.

**Table 4**
Dynamic analysis: percentage raw material purchased from each supplier under different SC configurations.

| | Relative importance of the economic goal | Situation | Ch1 | Ch2 | Ch3 | Ch4 | Ch5 | Ch6 | V1 | V2 | V3 | V4 | V5 | C1 | C2 | C3 | C4 | C5 | B1 | B2 | B3 | B4 | B5 | B6 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| The business-as-usual performance is significantly more | Significantly more important | Business-as-usual | | | | | | | 3.1 | 6.6 | | | 2.5 | 2.8 | | 8.8 | 22.8 | 23.8 | 2.5 | 1.4 | | 3.8 | 10.5 | 11.4 |
| | | Disruptions | 2.0 | 3.6 | 6.1 | 4.9 | 3.1 | 4.6 | 2.4 | 3.3 | 3.9 | 3.6 | 3.0 | 2.9 | 5.1 | 5.5 | 6.4 | 6.5 | 1.8 | 3.9 | 6.0 | 6.4 | 7.8 | 7.2 |
| | Moderately more important | Business-as-usual | | | | | | | | | | | 5.4 | 0.4 | | 8.8 | 20.4 | 26.3 | 2.5 | 3.1 | 3.5 | 7.7 | 10.5 | 11.4 |
| | | Disruptions | | | | | | | 2.3 | 4.4 | 4.3 | 4.1 | 8.7 | 1.9 | 2.8 | 6.1 | 11.5 | 14.5 | 4.5 | 3.5 | 4.1 | 6.7 | 9.8 | 10.8 |
| | Slightly more important | Business-as-usual | | | | | | | | | | | 5.4 | 0.4 | | 8.8 | 20.4 | 26.2 | 2.6 | 3.1 | 3.7 | 7.5 | 10.5 | 11.4 |
| | | Disruptions | | | | | | | 4.2 | 6.3 | 3.4 | 3.3 | 7.5 | 1.9 | 1.8 | 5.0 | 8.9 | 17.0 | 4.3 | 4.1 | 5.2 | 6.4 | 8.3 | 12.4 |
| | Equally important | Business-as-usual | | | | | | | | | | | 5.8 | | | 8.7 | 20.4 | 26.3 | 2.6 | 3.1 | 5.6 | 5.6 | 10.5 | 11.4 |
| | | Disruptions | | | | | | | 0.4 | 4.3 | 0.9 | 1.0 | 3.9 | 0.5 | 0.8 | 7.9 | 15.3 | 22.2 | 2.4 | 2.8 | 4.8 | 6.2 | 9.8 | 16.8 |
| The business-as-usual performance is moderately more | Significantly more important | Business-as-usual | | | | | | | 5.2 | 6.6 | | | 3.3 | | 1.4 | 8.8 | 20.4 | 26.3 | 2.6 | 3.1 | | 1.4 | 10.5 | 10.4 |
| | | Disruptions | 1.5 | 2.5 | 3.7 | 6.9 | 4.2 | 4.9 | 3.8 | 3.2 | 2.7 | 3.6 | 4.5 | 1.7 | 6.3 | 6.8 | 7.6 | 5.1 | 3.4 | 5.5 | 6.2 | 4.6 | 6.6 | 4.7 |
| | Moderately more important | Business-as-usual | | | | | | | 2.9 | 6.6 | | | 2.7 | 2.8 | | 8.8 | 22.7 | 14.5 | 2.6 | 0.5 | | 4.6 | 10.5 | 20.8 |
| | | Disruptions | 2.1 | 3.5 | 1.5 | 5.4 | 4.6 | 5.2 | 4.0 | 3.0 | 2.9 | 4.0 | 3.9 | 2.2 | 6.5 | 5.8 | 4.1 | 8.9 | 2.8 | 5.4 | 4.1 | 5.5 | 8.2 | 6.4 |
| | Slightly more important | Business-as-usual | | | | | | | | | | | 6.1 | | | 8.8 | 20.4 | 26.3 | 2.6 | 2.9 | 7.0 | 4.0 | 10.5 | 11.4 |
| | | Disruptions | | | | | | | 3.9 | 5.2 | 5.4 | 5.8 | 10.2 | 2.6 | 3.8 | 3.2 | 8.3 | 10.4 | 4.1 | 4.0 | 5.7 | 5.5 | 10.0 | 11.9 |
| | Equally important | Business-as-usual | | | | | | | | | | | 5.9 | | | 8.6 | 22.8 | 23.9 | 2.6 | 3.1 | 3.5 | 7.7 | 10.5 | 11.4 |
| | | Disruptions | | | | | | | 5.0 | 3.2 | 5.5 | 7.8 | 7.8 | 2.5 | 3.7 | 5.8 | 10.9 | 12.7 | 4.6 | 3.8 | 5.6 | 5.1 | 6.6 | 9.4 |
| The business-as-usual performance is slightly more important | Significantly more important | Business-as-usual | | | | | | 7.7 | | | | 6.5 | 13.1 | | | | 20.4 | 26.3 | 2.6 | | 0.2 | 3.9 | 7.9 | 11.4 |
| | | Disruptions | 2.3 | 3.0 | 3.1 | 3.3 | 7.2 | 5.6 | 2.5 | 3.6 | 6.0 | 7.2 | 6.9 | 1.7 | 6.4 | 2.7 | 7.4 | 6.2 | 2.5 | 2.3 | 2.1 | 4.0 | 5.2 | 8.8 |
| | Moderately more important | Business-as-usual | | | | | 5.7 | | | | | 8.8 | 13.1 | | | | 20.3 | 26.3 | 2.6 | | 0.1 | 3.9 | 9.3 | 9.9 |
| | | Disruptions | 2.6 | 1.0 | 1.6 | 3.7 | 5.6 | 11.3 | 2.9 | 2.6 | 4.4 | 7.8 | 8.8 | 3.8 | 2.8 | 1.2 | 6.5 | 11.6 | 5.5 | 4.0 | 3.3 | 2.2 | 1.6 | 5.2 |
| | Slightly more important | Business-as-usual | | | | | | 5.4 | | | | 8.8 | 13.1 | | | | 20.4 | 26.3 | 2.6 | | 0.2 | 3.9 | 8.0 | 11.3 |
| | | Disruptions | 2.0 | 0.3 | 2.7 | 4.2 | 5.4 | 10.9 | 1.7 | 2.5 | 2.9 | 6.1 | 11.8 | 1.2 | 2.4 | 5.0 | 8.5 | 8.0 | 0.3 | 1.8 | 2.0 | 5.8 | 6.1 | 8.4 |
| | Equally important | Business-as-usual | | | | | 2.3 | | | | | 8.8 | 16.7 | | | 3.7 | 11.3 | 26.3 | 2.5 | | | 6.3 | 5.3 | 16.8 |
| | | Disruptions | 1.0 | 0.6 | 2.5 | 3.1 | 6.2 | 8.5 | 2.8 | 4.3 | 2.1 | 3.7 | 12.7 | 1.0 | 1.5 | 3.8 | 8.3 | 15.3 | 1.8 | 1.4 | 3.4 | 4.1 | 5.0 | 6.9 |
| The business-as-usual performance is equally important | Significantly more important | Business-as-usual | | | | 0.2 | 12.8 | 20.8 | 0.1 | 3.3 | 7.4 | 8.8 | 26.3 | | | | 1.2 | 13.1 | | | | | 0.3 | 5.7 |
| | | Disruptions | 0.1 | 1.0 | 3.4 | 3.4 | 11.3 | 14.8 | 3.0 | 3.9 | 6.0 | 8.0 | 18.4 | 0.5 | 1.7 | 3.5 | 4.1 | 8.0 | 0.2 | 0.2 | 0.5 | 1.1 | 2.3 | 4.6 |
| | Moderately more important | Business-as-usual | | | | | 12.7 | 20.8 | 0.1 | 3.3 | 7.4 | 8.8 | 26.3 | | | | 1.5 | 13.1 | | | | | 0.3 | 5.7 |
| | | Disruptions | 0.9 | 0.1 | 2.4 | 6.2 | 6.4 | 15.3 | 1.6 | 4.0 | 4.4 | 5.3 | 16.1 | 1.6 | 3.5 | 6.3 | 2.3 | 10.7 | 1.8 | 1.1 | 2.3 | 0.6 | 0.9 | 6.2 |
| | Slightly more important | Business-as-usual | | | | | 10.0 | 22.2 | | 1.8 | 7.4 | 8.8 | 26.3 | | | | 2.9 | 13.1 | | | | | 1.8 | 5.7 |
| | | Disruptions | 0.4 | 0.1 | 1.3 | 7.1 | 12.7 | 17.1 | 1.4 | 2.4 | 4.7 | 8.5 | 18.1 | 0.1 | 0.2 | 1.7 | 6.1 | 8.7 | 0.1 | | 0.4 | 1.7 | 2.0 | 5.2 |
| | Equally important | Business-as-usual | | | | | 12.8 | 20.8 | | 0.7 | 7.4 | 8.8 | 26.3 | | | | 1.4 | 13.1 | | | | | 3.0 | 5.7 |
| | | Disruptions | | | 0.1 | 2.4 | 12.4 | 19.8 | 0.2 | 3.2 | 6.9 | 8.1 | 24.2 | | | 0.1 | 3.5 | 12.6 | | | | 0.1 | 0.9 | 5.5 |

**Table 5**
Dynamic analysis: changes in facility location/capacity decisions when varying the relative importance of the economic goal and the relative importance of the business-as-usual performance.

| Relative importance of the business-as-usual performance | Relative importance of the economic goal | Factories | | | | DCs | | |
|---|---|---|---|---|---|---|---|---|
| | | m1 | m2 | m3 | m4 | w1 | w2 | w3 |
| Significantly more important | Significantly more important | S[a] | S | M | M | S | M | M |
| | Moderately more important | | L | L | L | S | M | M |
| | Slightly more important | | L | L | L | S | M | M |
| | Equally important | | L | L | L | S | L | S |
| Moderately more important | Significantly more important | S | S | M | M | S | M | M |
| | Moderately more important | S | S | M | M | S | M | M |
| | Slightly more important | | L | L | L | S | M | M |
| | Equally important | | L | L | L | M | M | S |
| Slightly more important | Significantly more important | S | S | M | M | S | M | M |
| | Moderately more important | S | S | M | M | S | M | M |
| | Slightly more important | S | S | M | M | S | M | M |
| | Equally important | S | S | M | M | S | M | M |
| Equally important | Significantly more important | S | M | M | S | S | M | M |
| | Moderately more important | S | M | M | S | S | M | M |
| | Slightly more important | M | M | S | S | S | M | M |
| | Equally important | M | M | S | S | S | M | M |

[a] Facility sizes L: Large, M: Medium, S: Small.

scenarios. This being said, a total of 108 individual model runs ($4 * 1 + 4 * 26$) were completed to obtain the required data for this dynamic tradeoff analysis.

In the dynamic tradeoff analysis demands of all products in all markets are fully satisfied in all supply disruption scenarios; thus, no lost sales occur in disruptions. This even holds true for a situation when the business-as-usual performance is perceived by the decision maker as significantly more important than the performance in disruptions. This is an important remark because our static tradeoff analysis found no SC configuration that fulfills the entire demand in disruptions (see Fig. 3). But, now the question is asked – what is the cost of satisfying product demand in disruption situations? This is what Fig. 4 can answer.

Two general observations from Fig. 4 include: (1) in all cases, the greater the relative importance of the economic goal, the lower the SC cost and the poorer the environmental and social performance in business-as-usual and disruption situations and (2) in most cases, the higher the relative importance of the business-as-usual performance, the more significant the average expected SC cost in disruptions. While these observations may not seem surprising at first glance, we discuss in this section how they help a decision maker perform a comparative analysis for making more effective and informed sourcing and network design decisions.

Let us discuss how the proposed dynamic tradeoff methodology has helped ACO management develop a resiliently sustainable SC. In a static tradeoff analysis for ACO, the economic goal was perceived as moderately more important than the non-economic goals. From Fig. 2 and Table 3, the design and operation of this network could cost \$943,221 when opening two small factories in Vietnam and Bangladesh and a medium factory in Cambodia. From Table 2, the SC works with 10 suppliers in three different countries.

Looking at the results for dynamic tradeoff analysis, for a situation where the economic goal is moderately more important (Fig. 4c and d), there are four configurations corresponding to different importance degrees of the business-as-usual performance. Let us now look at the SC structure and performance in a situation where the business-as-usual performance is moderately more important than performance in disruptions. In this case, the SC cost in business-as-usual is equal to \$953,211; while under disruptions the expected SC cost, on average, may rise to \$993,240 to enable the SC to fulfill the demands of all markets by adjusting the sourcing, production and distribution strategies. This configuration opens four factories, including two small factories in China and Vietnam and two medium factories in Cambodia and Bangladesh (see Table 5). In business-as-usual, 12 suppliers provide the required raw material to the factories; whilst the material sourcing strategies and the level of supplier engagements is attuned in disruptions depending on the disaster magnitude and the number of suppliers affected (see Table 4).

Comparing the two aforementioned configurations, we find that transition from a "sustainable SC" to a "resiliently sustainable SC" implies that (1) the SC cost in business-as-usual increases by about 1%, from \$943,221 in static tradeoff analysis to \$953,211 in dynamic tradeoff analysis, (2) in disruptions, a resiliently sustainable SC is able to satisfy the demands of all markets at a 4.2% cost increase, from \$953,211 to \$993,240, by adjusting the sourcing, production and distribution strategies, (3) the engagement of more raw material suppliers in a resiliently sustainable SC allows for the unaffected suppliers to make up the supply shortage in disruptions, i.e., switching material requisition amongst the suppliers, and (4) the environmental and social performance of the SC remains almost unaffected in the face of disruptions.

Overall, for the proposed case study and its parametric data, our dynamic sustainability tradeoff analysis shows that a small increase in the business-as-usual cost of the SC (in this case only 1%) can bring about the development of a resiliently sustainable SC whose economic and non-economic performance is only lightly affected in the face of unforeseen disruptions. The only downside in this case is the marginally higher EPS and SPS values in the static tradeoff analysis (8.5 and 8.1 in static analysis versus 8.1 and 7.7 in the dynamic analysis). If this is seen as a major drawback, especially for sustainability reporting purposes, the management can look into the configurations in which the economic goal is slightly more important that the non-economic goals (Fig. 4e and f). Under these configurations, a minor SC cost increase can ensure a matched SC sustainability performance.

## 5. Conclusions: Moving towards a resiliently sustainable supply chain

Sustainability has been the main focus of most industrial initiatives and innovations. What is not quite well understood is the fact that sustainable SC practices in a rapidly changing global environment necessitate moving beyond a simplistic static sustainability analysis, towards a "dynamic analysis" which facilitates studying the sustainability performance of a SC in the face of unpredictable disruptions. This article presented an early attempt for integrated sustainability–resilience analysis at the strategic SC design level.

A multi-objective mathematical model was introduced that uses a sustainability performance scoring approach to quantify the environmental and social performance of the SC. A stochastic fuzzy goal programming approach was presented to seek tradeoff solutions for developing a resiliently sustainable SC. The stochastic and fuzzy aspects of the proposed methodology can help address the co-occurrence of uncertainty in disruption likelihood and imprecise weights of economic, environmental and social sustainability goals. The application of the proposed model and methodology was investigated in a real world case study. Static and dynamic sustainability tradeoff analyses were completed to explore what it takes to develop a resiliently sustainable SC.

The numerical results from the empirical case study showed that the static sustainability tradeoff analysis can be simplistic and impractical. A sustainable SC designed through a static tradeoff analysis was unable to satisfy product demands in the face of supply disruptions. However, a resiliently sustainable SC developed through a dynamic sustainability tradeoff analysis was able to satisfy the entire market demand at a slight increase in overall SC cost through the adjustment of sourcing, production and distribution strategies when disruptions occur. In addition, we observed that the environmental and social performance of the resiliently sustainable SC remained almost unaffected in disruptions.

While we have shown the utility of the proposed model and methodology in developing a resiliently sustainable SC, our study and investigation is not without limitations. These limitations can provide directions for future work in this important area of research. A thorough dynamic tradeoff analysis requires examining the SC sustainability imbalance under several disruption scenarios. Such analysis can become a formidable challenge as the number of scenarios increase, especially if looking at different types of disruptions or situations where facilities are affected differently when disruptions occur. In addition, we studied the nexus of SC sustainability and resilience at the strategic design level. Similar analyses and tradeoff investigations can be completed at the tactical and operational planning levels to explore how tradeoff decisions can be affected by short-term and frequent supply, demand and lead-time variations/interruptions. Finally, investigating the possible extensions and applications of the proposed stochastic fuzzy goal programming approach can help its broader managerial acceptance and adoption in real world situations.

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