International Journal of Production Research

ISSN: 0020-7543 (Print) 1366-588X (Online) Journal homepage: http://www.tandfonline.com/loi/tprs20

Selection of a dynamic supply portfolio under delay and disruption risks

Tadeusz Sawik

To cite this article: Tadeusz Sawik (2018) Selection of a dynamic supply portfolio under delay and disruption risks, International Journal of Production Research, 56:1-2, 760-782, DOI: 10.1080/00207543.2017.1401238

To link to this article: https://doi.org/10.1080/00207543.2017.1401238

Published online: 17 Nov 2017.

Submit your article to this journal

Article views: 80

View related articles

View Crossmark data

Citing articles: 2 View citing articles

Full Terms & Conditions of access and use can be found at
http://www.tandfonline.com/action/journalInformation?journalCode=tprs20

International Journal of Production Research, 2018
Vol. 56, Nos. 1–2, 760–782, https://doi.org/10.1080/00207543.2017.1401238

Taylor & Francis
Taylor & Francis Group

Check for updates

Selection of a dynamic supply portfolio under delay and disruption risks

Tadeusz Sawik*

Department of Operations Research, AGH University of Science & Technology, Kraków, Poland

(*Received 10 March 2017; accepted 27 October 2017*)

The problem of a multi-period supplier selection and order quantity allocation in the presence of supply chain disruption and delay risks is considered. Given a set of customer orders for finished products, the decision-maker needs to decide from which supplier and when to deliver product-specific parts required for each customer order to meet customer requested due date at a low cost or a high service level and to mitigate the impact of supply chain risks. For the selection of risk-neutral or risk-averse dynamic supply portfolio, a scenario-based stochastic mixed integer programming approach is developed. In the scenario analysis, the low probability and high impact supply disruptions are combined with the high probability and low impact supply delays. The risk-neutral portfolio is optimised by minimising expected cost or maximising expected service level. The risk-averse portfolio is optimised by calculating cost- or service-at-risk and minimising conditional cost-at risk or maximising conditional service at risk. The proposed dynamic portfolio approach leads to a time-indexed stochastic MIP formulation with a strong LP relaxation, which has proven to be computationally very efficient. The findings indicate that neglecting potential delay risks in supplier selection may lead to greater supply fluctuations and manufacturing delays.

Keywords: disruption management; supply chain risk management; supplier selection; stochastic programming; mixed integer linear programming

1. Introduction

Supply chain risk management has been extensively studied over the past decade. Research addresses the two risk levels (e.g. Tang 2006; Stecke and Kumar 2009; Gurnani, Mehrotra, and Ray 2012): operational risks or disruption risks. Operational risks are referred to the inherent uncertainties arising from the problems of coordinating supply and demand such as uncertain customer demand, uncertain supply, uncertain cost, and uncertain lead-time and delay. Disruption risks are referred to the major disruptions to normal activities (disruptions of material flows, information flows) caused by natural and man-made disasters such as earthquakes, floods, hurricanes, etc. or equipment breakdowns, economic crises such as currency evaluation, labour strikes, terrorist attacks. In most cases, the business impact associated with disruption risks is much greater than that of the operational risks (e.g. Fujimoto and Park 2013; Park, Hong, and Roh 2013; Matsuo 2015; Marszewska 2016).

Unlike disruptions, delays are referred to relatively periodic events, originating directly from internal activities of companies and/or relationships within partners in the supply chain. In particular, the high probability supply delays may have a significant impact in a make-to-order manufacturing and just-in-time environment. A delay in the supply of raw materials, parts or components can lead to longer lead times, rescheduling decisions, congestion at the shop floor, decrease of service level and consequently to lower profits. Moreover, if any delays occur, waste may increase due to shutdown of production lines. A successful just-in-time implementation requires a multi-period supplier selection and supplier performance evaluation tools (e.g. Aksoy and Ozturk 2011).

Quang and Hara (2017) define delays in supply chain activities as time risk that may detrimentally affect supply chain performance. The authors emphasise that the delay risk should be considered in terms of time series, which is useful in forecasting how many delays and of what length are incurred and likely to occur, and quantifying them within a specific period of time (e.g. transportation delays due to seasonal weather conditions). Delays in materials and equipment procurement are often a contributory cause of cost overruns in construction projects (e.g. Manavazhi and Dinesh 2002). In contrast to project management, where a joint impact of disruption and delay is often studied (e.g. Eden et al. 2000), in the literature on supplier selection the two types of risks are usually considered separately. The problem of a multi-period supplier selection and order quantity allocation in the presence of supply chain delay and disruption risks is rarely reported in the literature (see, Section 2). The reason for that can be due to a more complex decision-making that requires to simultaneously consider the high probability and low impact supply delays and the low probability and high impact supply disruptions. In practice, the multiple deliveries from each supplier can be replaced by a single batch delivery, where different orders are batched together

*Email: ghsawik@cyf-kr.edu.pl

© 2017 Informa UK Limited, trading as Taylor & Francis Group

for direct shipping (e.g. Sawik 2016b). Moreover, when suppliers rely on 3PL providers, a fixed pre-specified delivery date or delivery time window can be considered. Nevertheless, it is common in the make-to-order manufacturing to use penalties that are proportional to the amount of days the delivery exceeded the delivery date. In particular, when all suppliers are similarly exposed to high impact disruption risks, then the low impact delay risk may predominate the supplier selection decision. Moreover, a long delay in supply activities can be considered a supply disruption, and vice versa a long recovery time from a disruption leads to long supply delays. Such phenomena can also be analysed in the framework of supply chain disruption propagation (see, Scheibe and Blackhurst 2017) or the ripple effect (e.g. Levner and Ptuskin 2017). For example, in Toyota supply chain, many suppliers are similarly exposed to low probability regional disruption risks due to seismic hazard in different Japanese prefectures (Marszewska 2016). Then, the supplier reliability of on-time delivery and the associated delay risk become important criteria for supplier selection in just-in-time environment. For example, to reduce dependency on external suppliers and attain the capacity to absorb supply fluctuations Toyota invested in the technology necessary to produce higher-end electronic components in-house (Ahmadjian and Lincoln 2001).

In this paper, the static (single-period) portfolio approach and the scenario-based stochastic mixed integer programming (MIP) formulations presented in Sawik (2011b, 2011c, 2011d) are enhanced for a multi-period supplier selection and order quantity allocation in the presence of both the low probability and high impact supply chain disruption risks and the high probability and low impact supply chain delay risks. In this study the combined disruptions and delays of supply are modelled by multinomial ('on-time or different length delay or never') random variables to account for random delays of different length where, by convention, delays longer than a pre-specified threshold are considered disruptions. Time-indexed, stochastic MIP models are developed for selection of:

- the risk-neutral dynamic supply portfolio to minimise expected cost or maximise expected service level;
- the risk-averse dynamic supply portfolio to minimise conditional cost-at-risk or to maximise conditional service-at-risk.

The paper is organised as follows. The review of relevant literature is presented in Section 2. The problem of selection a dynamic supply portfolio in the presence of supply chain delay and disruption risks is described in Section 3. The stochastic binary or mixed integer programs for selection of risk-neutral and risk-averse dynamic supply portfolio are provided in Section 4. In Section 5 the general 'on-time or different length delay or never' multinomial delivery scenarios are illustrated with numerical examples and compared with worst-case 'longest delay or never' binomial disruption scenarios. Finally, conclusions and managerial implications, as well as directions for further research are reported in Section 6.

2. Literature review

The following four basic approaches can be applied in practice mitigate the impact of supply chain risks (Tang 2006): supply management, demand management, product management and information management. In particular, to ensure efficient supply of materials along a supply chain, supply chain management deals with selection of a supply portfolio, i.e. supplier selection and order quantity allocation under uncertain quality of supplied materials and reliability of on-time delivery (e.g. Aissaoui, Haouari, and Hassini 2007; Ho, Xu, and Dey 2010). Hamdi et al. (2015) reviewed the literature in the field of supplier selection under supply chain risk management. A collection of 124 papers from 2003 to 2014 was analysed and classified, first, according to the characteristics of the problem they deal with, secondly, according to the approach they propose, and thirdly, according to the techniques they use. A recent literature review on Operations Research/Management Science models for supply chain disruptions was presented by Snyder et al. (2016).

The supplier selection and order quantity allocation problem is a complex stochastic combinatorial optimisation problem. For example, chance-constrained programming models were developed by Kasilingam and Lee (1996) to account for stochastic demand and by Wu and Olson (2008) to consider expected losses from quality acceptance inspection or late delivery. Parlar and Perry (1996) presented a continuous time model in which the availability of each of the m suppliers is uncertain because of disruptions such as equipment breakdown. By considering the case that each supplier is either 'on' or 'off', there are 2^m possible number of states for the whole system. For each of these 2^m states, they analyse a state-specific (s, Q) ordering policy so that the buyer would order Q units when the on-hand inventory reaches s. The risks associated with a supplier network was studied by Berger, Gerstenfeld, and Zeng (2004), who considered catastrophic super events that affect all suppliers, as well as unique events that impact only one single supplier, and then a decision tree-based model was presented to help determine the optimal number of suppliers needed for the buying firm. Ruiz-Torres and Mahmoodi (2007) considered unequal failure probabilities for all the suppliers. Berger and Zeng (2006) studied the optimal supply size in a single or multiple sourcing strategy context, under a number of scenarios that are determined by various financial loss functions, the operating cost functions and the probabilities of all the suppliers being down. Yu, Zeng, and Zhao (2009) considered the impacts of supply disruption risks on the choice between the single and dual sourcing methods in a two-stage supply chain with a non-stationary and price-sensitive demand. Yue, Xia, and Tran (2010) introduced frontier sourcing portfolios to support manufacturers sourcing decisions, which consider the cost and probability of finishing the order on time. Ravindran et al. (2012) developed multi-criteria supplier selection models incorporating supplier risks. In the multi-objective formulation, price, lead-time, disruption risk due to natural event and quality risk are explicitly considered as four conflicting objectives that have to be minimised simultaneously. Four different variants of goal programming were used to solve the multi-objective optimisation problem. Xanthopoulos, Vlachos, and Iakovou (2012) developed newsvendor-type inventory models for capturing the trade-off between inventory policies and disruption risks in a dual-sourcing supply chain network, where both supply channels are subject to disruption risks. The models were developed for both risk-neutral and risk-averse decision-making. Li and Zabinsky (2011) developed a two-stage stochastic programming model and a chance-constrained programming model to determine a minimal set of suppliers and optimal order quantities. Both models include several objectives and strive to balance a small number of suppliers with the risk of not being able to meet demand. The stochastic programming model is scenario-based and uses penalty coefficients, whereas the chance-constrained programming model assumes a probability distribution and constrains the probability of not meeting demand. Hammami,Temponi, and Frein (2014) proposed a scenario-based stochastic model for supplier selection in the presence of uncertain fluctuations of currency exchange rates and price discounts. Meena, Sarmah, and Sarkar (2014) studied the problem of determining the number of suppliers under risks of supplier failure due to catastrophic events. The authors considered different failure probability, capacity and capacity specific compensation potential. They proposed an algorithm to determine the optimal number of suppliers assuming an equal allocation among the selected suppliers.

In the literature on supply chain risk management, the supply is either subject to complete disruptions or yield uncertainty. Yield uncertainty occurs when the quantity of supply delivered is a random variable, modeled as either a random additive or multiplicative quantity, whereas disruptions occur when supply is subject to partial or complete failure (e.g. Sawik 2015). Typically disruptions are modelled as binary (all-or-nothing) events which occur randomly and may have a random length. Schmitt and Snyder (2012) considered inventory systems subject to both supply disruptions and yield uncertainty.

A model for the quantification of disruption risk in a global supply chain was proposed by Mizgier, Wagner, and Matthias (2015). To calculate the loss distribution induced by supply chain disruptions, they applied a bottom-up modelling approach, incorporated the network structure explicitly and defined the loss propagation between the firms. They showed that diversification effects can lead to counterintuitive results when the network structure and the correlations of disruptive events are considered. In a recent paper, Wagner, Mizgier, and Papageorgiou (2017) distinguished between operational disruptions and operational risks that include internal operational risks and supply chain operational risks. Namdar et al. (2017) developed a scenario-based mathematical model for single and multiple sourcing in the presence of disruption and operational risks. The various sourcing strategies were investigated to achieve supply chain resilience under disruptions. The strategies considered were single and multiple sourcing, backup supplier contracts, spot purchasing and collaboration and visibility.

Fattahi, Govindan, and Keyvanshokooh (2017) considered a multi-period design of a supply chain network under both disruption and operational risks. The operational risk is due to inherent uncertainties in some parameters such as demand, supply, costs and lead-time. The uncertainty related to stochastic parameters has been realised progressively in each time period and a multi-stage stochastic programming was applied for optimisation of supply chain design.

In a recent paper, Dupont et al. (2017) focused on the insurance versus profitability trade-off faced by a supply manager who buys from suppliers for the outlets. The authors used a MIP approach to provide decision-making support that shows a supply manager the elasticity of expected losses versus expected profits. Using the proposed approach a supply manager of known risk aversion can make better decisions when choosing suppliers under disruption risks.

The vast majority of the decision models developed for supplier selection and order quantity allocation are single-period (static) models (e.g. Demirtas and Ustun 2008; Sawik 2011b, 2011c) that do not consider inventory management. In contrast to the multi-period (dynamic) models (e.g. Ustun and Demirtas 2008; Che and Wang 2008) that may consider the inventory management by lot-sizing and scheduling of orders. For custom-engineered products, however, no inventory of custom parts can be kept on hand. Instead, the custom parts often need to be requisitioned with each customer order and hence the custom parts inventory need not to be considered.

Sawik (2011b, 2011c), proposed a portfolio approach for the supplier selection and order quantity allocation under disruption risks and under operational risks, respectively. The two popular in financial engineering percentile measures of risk, value-at-risk (VaR) and conditional value-at-risk (CVaR) (e.g. Sarykalin, Serraino, and Uryasev 2008) were applied for managing the risk of supply disruptions or supply delays.

The supplier selection problem is highly dynamic in real practice. For example, the customer demand, supplier capacity, lead time, price, discounts and quality of supplying parts may vary over time. The supplier selected for one period may not necessarily be selected for the next period to supply the same set of parts. The integrated scheduling of orders over time with the supplier selection may significantly reduce cost for a multi-period planning horizon. For example, Sen et al. (2014) developed a scenario-based multi-stage stochastic optimisation model for multi-period supplier selection under price uncertainty that allows to consider random events such as a drop in price, a price change in the spot market or a new discount offer. The model was used to purchase a large volume of multiple items over multiple periods from multiple suppliers that provide base prices and discounts.

The idea of a dynamic supply portfolio approach in the presence of both the low probability and high impact supply disruptions and the high probability and low impact supply delays was presented by Sawik (2011d) for a multi-period supplier selection and order quantity allocation in a make-to-order environment. For the selection of a dynamic supply portfolio, a stochastic MIP was proposed to incorporate risks via scenario analysis. In the scenario analysis, both types of the supply chain risks are considered simultaneously. The disruption and delay risks were incorporated utilising the concepts of percentile measures of risk, VaR and CVaR. In Sawik (2011d), the cost-oriented objective function was considered only and general delivery scenarios with on time, delayed or no supplies. The delays were modelled as statistically independent, discrete multivariate random variables. In addition to the general scenarios, the two special subsets of the scenarios were considered, with at most one disruption of each supplier over the horizon and with multiple consecutive disruptions of each supplier over the horizon since its first disruption. The special delivery scenarios with no delays or with the longest delays were analysed. Rabbani et al. (2014) proposed a combination of two models by Sawik (2010b, 2011d) to consider a multi-period supplier selection and order allocation problem. The combined model finds the optimal dynamic supply portfolio, and also accounts for the quantity and business volume discounts offered by suppliers. A dynamic supplier selection problem was also considered by Ware, Singh, and Banwet (2014), who developed a mixed-integer non-linear programming model that incorporates risk associated with fluctuating demand, supply disruption, quality failure probability and delivery delay. In a related study, Tsai (2016) presented a formulation that helps to mitigate supply failure by considering a dynamic model-based optimisation approach, in which the risk of supply interruption is time-dependent. The proposed model supports decision-making on how many standby suppliers are ideal in the presence of supply chain disruption risk.

The stochastic dynamic supply portfolio approach is similar to deterministic single-customer direct shipping method, with individual and immediate delivery of each order to customer, immediately upon its completion. The variety of deterministic models that integrate manufacturing and delivery operations at the detailed scheduling level, including the direct shipping models, was presented in Chen (2010). The models were classified by shipping and delivery methods. Such models attempt to optimise manufacturing and delivery scheduling jointly by taking into account relevant costs and customer service levels. However, they do not consider any type of supply chain risks.

In Sawik (2016a, 2017) the problem of selection a static supply portfolio under all-or-nothing disruptions and selection of both primary and recovery static supply portfolios under multilevel disruptions, respectively, was combined with scheduling of customer orders.

In this paper, the static portfolio approach and the scenario-based stochastic MIP formulations presented in Sawik (2011b, 2011c) are enhanced for a multi-period supplier selection and order quantity allocation in the presence of both the low probability and high impact supply chain local and regional disruption risks and the high probability and low impact supply chain local delay risks. The problem of selection a dynamic supply portfolio considered in this paper is essentially different from that described in Sawik (2011d). Now, the supplies are subject to local delivery delay risks, and both local and regional delivery disruption risks. While supply disruptions are typically modeled by binomial (all-or-nothing) random variables, (e.g. Chahar and Taaffe 2009) the combined disruptions and delays of supply can be modelled by multinomial ('on-time or different length delay or never') random variables to account for random delays of different length. The probability of each delivery scenario is calculated assuming that each supplier may be simultaneously exposed to various types of supply chain risks. In addition to the cost-oriented objective function, an alternative service level objective is also considered, and the general 'on-time or different length delay or never' multinomial delivery scenarios are compared with worst-case 'longest delay or never' binomial disruption scenarios.

3. Problem description

The approach proposed in this paper can be applied for a very common type of supply chain, with a producer of single product, who obtains raw materials from several different suppliers with limited supply capacity to meet customer orders by customer requested due dates. However, the approach is also applicable to the case of a single producer, who assembles different types of products using product-specific parts purchased from multiple suppliers (for notation used, see Table 1). In order to simplify further considerations it is assumed that for each product type, one product-specific part type (e.g. a critical custom part type) needs to be supplied in required amount by custom parts manufacturers. For example, in the electronics industry producer of different electronic devices needs to be supplied by electronics manufacturers with printed wiring boards of different device-specific design. However, the last assumption can be easily relaxed to consider supplies of different product-specific part types required for each product type.

Table 1. Notation.

Indices		
i	=	supplier, $i \in I$
j	=	customer order, $j \in J$
s	=	delivery scenario, $s \in S$
t	=	planning period, $t \in T$
Input parameters		
c_{it}	=	capacity of supplier i in period t
d_j	=	demand for parts required for customer order j
D	=	$\sum_{j \in J} d_j$ - total demand for parts
$\underline{\delta}_j$	=	the earliest delivery date of parts for customer order j
δ_j	=	the latest delivery date of parts for customer order j
e_i	=	cost of ordering parts from supplier i
g_j	=	per unit penalty cost of delayed customer order j caused by delayed delivery of required parts
h_j	=	per unit penalty cost of unfulfilled customer order j caused by shortage of required parts
o_{ij}	=	unit price of parts for customer order j purchased from supplier i
ϵ_{ij}	=	per unit price reduction for each delayed part for customer order j from supplier i
$p_{i,\tau}$	=	local delay probability of τ periods for delivery of parts from supplier i, $\tau \in \{0, \dots, \overline{\tau}\}$
$p_{i,\overline{\tau}+1}$	=	local disruption probability of supplier i
p^r	=	regional disruption probability of all suppliers $i \in I^r$ in region r
π_i	=	$p^r + (1 - p^r) p_{i,\overline{\tau}+1}$, total disruption probability of supplier $i \in I^r, r \in R$
α	=	confidence level
τ	=	$0, \dots, \overline{\tau}$, delivery delay
ρ_i	=	expected defect rate of supplier i

Let $I = \{1, \dots, \overline{I}\}$ be the set of $\overline{I}$ suppliers and $J = \{1, \dots, \overline{J}\}$ the set of $\overline{J}$ customer orders for the finished products, known ahead of time. Each customer order $j \in J$ is described by the quantity d_j of required custom parts and their latest delivery date, δ_j, to ensure meeting the customer requested due date for products. The planning horizon consists of $\overline{T}$ periods and denote by $T = \{1, \dots \overline{T}\}$ the set of planning periods.

Each supplier can provide the producer with custom parts for all customer orders. However, the suppliers have different capacity and, in addition, differ in price and quality of purchased parts and in reliability of delivery. Let c_{it} be the capacity of supplier i in period t, e_i, cost of ordering parts from supplier i, o_{ij}, per unit price of custom parts for customer order j purchased from supplier i and ρ_i, the expected defect rate for supplier i.

The suppliers are assumed to be located in $\overline{R}$ disjoint geographic regions. Denote by $I^r \subseteq I$ the subset of suppliers in region $r \in R = \{1, \dots, \overline{R}\}$, where $\bigcup_{r \in R} I^r = I$. The supplies of parts are subject to random local delays or disruptions that are uniquely associated with a particular supplier, which may arise from equipment breakdowns, local labour strike, fires, etc. In addition to independent local delays and independent local disruptions of each supplier individually there are also potential regional disasters that may result in correlated regional disruption of all suppliers in the same region simultaneously. For example, such regional disaster events may include floods, hurricanes, earthquakes, and widespread labour strikes in a transportation sector.

The delivery of parts from each supplier $i \in I$ is subject to random delay of different length, $\tau \in \mathcal{T} = \{0, \dots, \overline{\tau}, \overline{\tau}+1\}$, i.e. parts ordered for period t are delivered in period $t + \tau$, where $\tau = 0$, represents on time delivery and $\tau = \overline{\tau}$, represents maximum delay that may occur. The delivery of parts is also subject to random disruptions, i.e. parts are not delivered at all. By convention, the dummy delay $\tau = \overline{\tau} + 1$, represents disruption of supplies, i.e. no delivery of parts. If the delivery of parts for customer order j occurs in period $t + \tau > \delta_j$, then the delivery is delayed and the producer is charged by the customer with contractual penalty, $g_j d_j (t + \tau - \delta_j)$, where g_j is the per unit and per period penalty cost of delayed customer order j caused by the delayed delivery of required parts. If supplies of parts for customer order j are disrupted (i.e. dummy delay of $\tau = \overline{\tau} + 1$ periods), then the producer is charged with the contractual penalty, $h_j d_j$, for unfulfilled order j, where h_j is the per unit penalty cost of unfulfilled customer order j caused by the shortage of required parts.

Denote by $S = \{1, \dots, \overline{S}\}$ the index set of all delivery scenarios, and by P_s the probability of delivery scenario $s \in S$. Each scenario $s \in S$ can be represented by an integer-valued vector $\tau_s = \{\tau_{1s}, \dots, \tau_{\overline{I}s}\}$, where $\tau_{is} \in \mathcal{T}$ is the length of delay from supplier $i \in I$ under scenario $s \in S$. When all potential delivery scenarios are considered, then $\overline{S} = (\overline{\tau} + 2)^{\overline{I}}$. For each scenario $s \in S$, the supplies from every supplier can be delayed or disrupted either by a local or a regional event. Denote by $I_s \subset I$ the subset of non-shutdown (non-disrupted) suppliers, who can deliver orders on time or delayed under scenario s.

Table 2. Problem variables.

First stage variables		
u_i	=	1, if an order for parts is placed on supplier i; otherwise $u_i = 0$ (supplier selection)
v_{ijt}	=	1, if parts required for customer order j are to be delivered by supplier i in period t; otherwise $v_{ijt} = 0$ (order assignment)
Auxiliary variables		
V_{it}	=	the fraction of total demand for parts ordered from supplier i to be delivered in period t (dynamic supply portfolio: allocation of total demand for parts among suppliers and over time)
VaR^c		Cost-at-Risk, the targeted cost such that for a given confidence level α, for $100\alpha\%$ of the scenarios, the outcome is below VaR^c
VaR^{sl}		Service-at-Risk, the targeted service level such that for a given confidence level α, for $100\alpha\%$ of the scenarios, the outcome is above VaR^{sl}
$\mathcal{C}_s$	$\geq$	0, the tail cost for scenario s, i.e. the amount by which costs in scenario s exceed VaR^c
$\mathcal{S}_s$	$\geq$	0, the tail service level for scenario s, i.e. the amount by which VaR^{sl} exceeds service level in scenario s

The probability P_s for delivery scenario $s \in S$ with the subset I_s of non-shutdown suppliers is

$$P_s = \prod_{r \in R} P_s^r. \tag{1}$$

P_s^r is the probability of realising of delivery scenario s for suppliers in I^r

$$P_s^r = \begin{cases} (1 - p^r) \prod_{i \in I^r} (p_{i,\tau_{is}}) & \text{if } I^r \bigcap I_s \neq \emptyset \\ p^r + (1 - p^r) \prod_{i \in I^r} p_{i,\overline{\tau}+1} & \text{if } I^r \bigcap I_s = \emptyset, \end{cases} \tag{2}$$

where $p_{i,\tau_{is}}$ is the probability of occurrence the delay of length τ_{is} periods from supplier i under scenario s. By convention, $p_{i,\overline{\tau}+1}$, is the probability of local disruption of supplier i. The parts ordered from supplier i can be delivered on-time with probability, p_{i0}, delayed with probability $\sum_{\tau=1}^{\overline{\tau}} p_{i\tau}$, or not delivered at all with probability $p_{i,\overline{\tau}+1} = 1 - \sum_{\tau=0}^{\overline{\tau}} p_{i\tau}$.

Denote by π_i the total disruption (shutdown) probability of every supplier $i \in I^r, r \in R$

$$\pi_i = p^r + (1 - p^r) p_{i,\overline{\tau}+1}; \; i \in I^r, r \in R. \tag{3}$$

The decision-maker needs to decide on the selection of part suppliers, on quantities of various custom parts to be ordered from each selected supplier and on delivery dates to minimise expected cost or maximise expected service level or to mitigate the impact of disruption risks by minimising the potential worst-case cost or maximising the potential worst-case service level.

4. Problem formulation

4.1 *Risk-neutral dynamic supply portfolio*

In this section, two stochastic IP models **DSP_E(c)** and **DSP_E(sl)** are presented for selection of a risk-neutral multi-period supply portfolio in the presence of supply delay and disruption risks to minimise expected cost or to maximise expected service level, respectively.

The decision-maker needs to select a dynamic supply portfolio, i.e. the allocation of orders for parts among the suppliers and among the planning periods (e.g. Sawik 2011d). We assume that for each customer order, all custom parts are provided by a single delivery from one supplier only.

The dynamic supply portfolio is defined below, (for definition of problem variables, see Table 2).

$$\{V_{it} : \; i \in I, t \in T\},$$

where

$$\sum_{i \in I} \sum_{t \in T} V_{it} = 1$$

and $0 \leq V_{it} \leq 1$ is the fraction of the total demand for parts ordered from supplier i for period t and V_{it} is determined by the custom parts assignment variables v_{ijt}

$$V_{it} = \sum_{j \in J} d_j v_{ijt} / D;\ i \in I. \quad (4)$$

The supply delays and disruptions may result in the shortage of required parts and the corresponding delay and shortage penalty costs of delayed or unfulfilled customer orders should be incorporated into the model. The producer does not need to pay for defective or undelivered parts and parts delivered late may be paid for at a reduced price. On the other hand, the producer can be charged with a high penalty cost for delayed or unfulfilled customer orders for products, caused by the shortage of required parts. In a make-to-order manufacturing no inventory of custom parts can be kept on hand and the parts are requisitioned with each customer order (e.g. Sawik 2011b) In addition, custom parts required for each customer order j are to be delivered within a time window $[\underline{\delta}_j, \delta_j]$ derived from the customer requested due date to further reduce any inventory holding cost. The delivery cannot be earlier than the earliest date $\underline{\delta}_j$ and the required parts are assumed to be processed as soon as they are delivered. Thus no overage costs can be considered, whereas delay or disruption penalty costs represent the underage costs (see, Sawik 2011d).

For each delivery scenario $s \in S$ and each customer order $j \in J$ to be supplied with parts by non-disrupted supplier $i \in I_s$ in period t (i.e. with $v_{ijt} = 1$), the penalty cost of delivery delayed by $1 \le \tau_{is} \le \overline{\tau}$ periods is given by

$$g_j \max\{0, t + \tau_{is} - \delta_j\} d_j,$$

i.e. deliveries later than δ_j are penalised only (e.g. Sawik 2011d).

The resulting total expected delay penalty cost over all delivery scenarios can be expressed by

$$\sum_{s \in S} \sum_{i \in I_s} \sum_{t \in T} \sum_{j \in J: \delta_j < t + \tau_{is}} P_s (g_j (t + \tau_{is} - \delta_j) - \epsilon_{ij}) d_j v_{ijt},$$

where the producer does not need to pay full price for late delivery of parts and hence the purchasing costs of those parts are reduced by ϵ_{ij} per unit for each delayed part for customer order j from supplier i.

The total expected penalty cost of unfulfilled customer orders due to shortage of required parts caused by supply disruptions is

$$\sum_{s \in S} \sum_{i \notin I_s} \sum_{j \in J} \sum_{t \in T} P_s (h_j - o_{ij}) d_j v_{ijt}.$$

In a risk-neutral operating conditions the overall quality of the supply portfolio can be measured by the expected cost per part, E^c, (5), or expected service level E^{sl}, (6).

$$\begin{aligned} E^c = & \sum_{i \in I} e_i u_i / D + \sum_{i \in I} \sum_{j \in J} \sum_{t \in T} o_{ij} d_j v_{ijt} / D \\ & + \sum_{s \in S} \sum_{i \in I_s} \sum_{t \in T} \sum_{j \in J: \delta_j < t + \tau_{is}} P_s (g_j (t + \tau_{is} - \delta_j) - \epsilon_{ij}) d_j v_{ijt} / D \\ & + \sum_{s \in S} \sum_{i \notin I_s} \sum_{j \in J} \sum_{t \in T} P_s (h_j - o_{ij}) d_j v_{ijt} / D \end{aligned} \quad (5)$$

$$E^{sl} = \sum_{s \in S} \sum_{i \in I_s} \sum_{j \in J} \sum_{t \in T: \underline{\delta}_j \le t + \tau_{is} \le \delta_j} P_s d_j v_{ijt} / D \quad (6)$$

The expected cost E^c includes, cost of ordering,

$\sum_{i \in I} e_i u_i / D$,

cost of purchasing non defective parts,

$\sum_{i \in I} \sum_{j \in J} \sum_{t \in T} o_{ij} d_j v_{ijt} / D$,

cost of delayed deliveries of parts,

$\sum_{s \in S} \sum_{i \in I_s} \sum_{t \in T} \sum_{j \in J: \delta_j < t + \tau_{is}} P_s (g_j (t + \tau_{is} - \delta_j) - \epsilon_{ij}) d_j v_{ijt} / D$,

and cost of shortage of parts due to supply disruptions (cost of unfulfilled customer orders less cost of non delivered parts),

$\sum_{s \in S} \sum_{i \notin I_s} \sum_{j \in J} \sum_{t \in T} P_s (h_j - o_{ij}) d_j v_{ijt} / D$.

The purchase orders for parts are assumed to be inflated by the reject rates $\rho_i, i \in I$ of defective parts, i.e. are equal to $\sum_{i \in I} \sum_{j \in J} \sum_{t \in T} (1 + \rho_i) d_j v_{ijt}$. However, since the producer does not need to pay for ordered and defective parts in the amount of $\sum_{i \in I} \sum_{j \in J} \sum_{t \in T} \rho_i d_j v_{ijt}$, and pays a reduced price for delayed parts in the amount of $\sum_{i \in I} \sum_{t \in T} \sum_{j \in J: \delta_j < t + \tau} d_j v_{ijt}$, the corresponding purchasing cost per part for delivered parts is simply given by

$$\sum_{i\in I}\sum_{j\in J}\sum_{t\in T} o_{ij}d_j v_{ijt}/D$$
$$-\sum_{s\in S}\sum_{i\in I_s}\sum_{t\in T}\sum_{j\in J:\delta_j<t+\tau_{is}} P_s\epsilon_{ij}d_j v_{ijt}/D - \sum_{s\in S}\sum_{i\notin I_s}\sum_{j\in J}\sum_{t\in T} P_s o_{ij}d_j v_{ijt}/D.$$

The expected service level, E^{sl}, (6), is a surrogate measure of expected customer demand fulfilment rate and represents the expected fraction of demand for parts fulfilled within delivery due window.

The stochastic IP models **DSP_E(c)** and **DSP_E(sl)** for a risk-neutral selection of dynamic supply portfolio to minimise expected cost or maximise expected service level, respectively, are presented below.

DSP_E(c): *Risk-neutral selection of* **D***ynamic* **S***upply* **P***ortfolio to minimise expected cost*

Minimise (5)
subject to

(1) *Selection of dynamic supply portfolio*:

(a) for each customer order the required parts must be delivered exactly once, (7), not earlier than the earliest and not later than the latest delivery date, (8),
(b) parts cannot be ordered from non-selected suppliers, (9),
(c) for each selected supplier the total quantity of ordered parts cannot exceed the supplier capacity, (10),
(d) at least one order should be assigned to each selected supplier, (11),

$$\sum_{i\in I}\sum_{t\in T} v_{ijt} = 1;\ \ j\in J \tag{7}$$
$$\sum_{i\in I}\sum_{t\in T:\underline{\delta}_j\le t\le\delta_j} v_{ijt} = 1;\ \ j\in J \tag{8}$$
$$v_{ijt}\le u_i;\ \ i\in I, j\in J, t\in T \tag{9}$$
$$\sum_{j\in J}(1+\rho_i)d_j v_{ijt}\le c_{it}u_i;\ \ i\in I, t\in T \tag{10}$$
$$\sum_{j\in J}\sum_{t\in T} v_{ijt}\ge u_i;\ \ i\in I \tag{11}$$

(2) *Integrality conditions*:

$$u_i\in\{0,1\};\ \ i\in I, t\in T \tag{12}$$
$$v_{ijt}\in\{0,1\};\ \ i\in I, j\in J, t\in T. \tag{13}$$

DSP_E(sl): *Risk-neutral selection of dynamic supply portfolio to maximise expected service level*

Maximise (6)
subject to (7)–(13).
A simple upper bound on the expected service level, E^{sl}, (6), is derived below.

Proposition 1

$$E^{sl}\le\min\left\{1,\sum_{r\in R}\sum_{i\in I^r}\sum_{t\in T}(1-p^r)(1-p_{i,\overline{\tau}+1})c_{it}/(1+\rho_i)D\right\}. \tag{14}$$

Proof. The supply portfolio selection constraints (10) imply that

$$\sum_{s\in S}\sum_{i\in I_s}\sum_{j\in J}\sum_{t\in T:\underline{\delta}_j\le t+\tau_{is}\le\delta_j} P_s d_j v_{ijt}/D$$
$$\le\sum_{r\in R}\sum_{i\in I^r}\sum_{j\in J}\sum_{t\in T:\underline{\delta}_j\le t+\tau_{is}\le\delta_j}(1-p^r)(1-p_{i,\overline{\tau}+1})d_j v_{ijt}/D$$
$$\le\sum_{r\in R}\sum_{i\in I^r}\sum_{t\in T}(1-p^r)(1-p_{i,\overline{\tau}+1})c_{it}u_i/(1+\rho_i)D$$

$$\leq \sum_{r \in R} \sum_{i \in I^r} \sum_{t \in T} (1 - p^r)(1 - p_{i,\overline{\tau}+1}) c_{it}/(1 + \rho_i) D,$$

where $(1 - p^r)(1 - p_{i,\overline{\tau}+1}) = 1 - \pi_i$, (3), is a non disruption probability of supplier $i \in I^r$.

Since E^{sl} cannot be greater than 1, its upper bound is 1, if $\sum_{r \in R} \sum_{i \in I^r} \sum_{t \in T} (1 - p^r)(1 - p_{i,\overline{\tau}+1}) c_{it}/(1 + \rho_i) D > 1$. □

Models **DSP_E(c)** and **DSP_E(sl)** are deterministic equivalent integer programs of two-stage stochastic integer programs with recourse (Birge and Louveaux 2011). The primary portfolio selection variables, u_i, v_{ijt}, are referred to as first-stage decisions. The second stage variables are simply demand allocation variables for realised disruption scenarios s, $\tilde{v}^s_{ijt}$; $i \in I, j \in J, t \in T, s \in S$, defined as follows

$$\tilde{v}^s_{ijt} = \begin{cases} v_{ij,t-\tau_{is}} & \text{if } i \in I_s, j \in J, t \in T, s \in S \\ 0 & \text{if } i \notin I_s, j \in J, t \in T, s \in S. \end{cases}$$

In view of the above definition, an explicit introduction of the second stage variables $\tilde{v}^s_{ijt}$ into the IP formulations is not required.

Notice that if for each customer order, all custom parts can be provided by multiple delivery from different suppliers, then the binary order assignment variables v_{ijt} should be redefined as fractional allocation variables denoting the fraction of total demand for parts required for customer order j to be delivered by supplier i in period t.

4.1.1 *Dynamic supply portfolio for 'on time-or-never' delivery scenarios*

The dynamic supply portfolio approach is particularly useful when supply delay risks need to be considered. Otherwise, the static supply portfolio may be a more appropriate approach (e.g. Sawik 2011b). For the pure 'on time-or-never' delivery scenarios (i.e. for disruption scenarios), with on time or no delivery, the proposed multi-period models for $\overline{I}$ suppliers and $\overline{T}$ planning periods can be transformed into equivalent single-period models for $m = (\overline{I})(\overline{T})$ suppliers. To this end, each pair of indices $(i, t), i \in I, t \in T$ should be replaced with a single index $k \in K$, where $K = \{1, \ldots, m\}$ represents the set of equivalent m single-period suppliers. In the proposed stochastic IP models, variables u_i, v_{ijt} should be replaced by u_k, v_{kj}, respectively. Then, the portfolio selection constraints (7), (8) are replaced by

$$\sum_{k \in K} v_{kj} = 1; \;\; j \in J$$

$$\sum_{k \in K_j} v_{kj} = 1; \;\; j \in J,$$

where K_j is the subset of equivalent single-period suppliers that are capable of delivering parts required for customer order j and it represents the subset $\{(i, t) : \; i \in I, \; \underline{\delta}_j \leq t \leq \delta_j\}$ of pairs (i, t) feasible for customer order j.

4.2 *Risk-averse dynamic supply portfolio*

In the risk-averse selection of supply portfolio under delay and disruption risks, the confidence level α is fixed by the decision maker to control the risk of losses due to supply delays and disruptions. We assume that the decision-maker is willing to accept only portfolios for which the the total probability of scenarios with costs greater than VaR^c or with service level lower than VaR^{sl} is not greater than $1 - \alpha$ (e.g. Sawik 2010a, 2012). Furthermore, a risk aversive decision-maker wants to minimise the expected worst-case costs exceeding VaR^c or to maximise the expected worst-case service level below VaR^{sl}.

Define by $\mathcal{C}_s$ the tail cost for scenario s, where tail cost is defined as the amount by which costs in scenario s exceed VaR^c. In a similar way, define by $\mathcal{S}_s$ the tail service level for scenario s, where tail service level is defined as the nonnegative amount by which VaR^{sl} exceeds service level in scenario s.

The portfolio will be optimised by calculating VaR^c and minimising CVaR^c simultaneously or by calculating VaR^{sl} and maximising CVaR^{sl}, respectively.

The stochastic MIP models **DSP_CV(c)** and **DSP_CV(sl)** for the risk-averse selection of supply portfolio to reduce the risk of high costs and the risk of low service level, respectively, are formulated below.

DSP_CV(c): *Risk-averse selection of dynamic supply portfolio to minimise CVaR of cost*

Minimise

$$CVaR^c = VaR^c + (1 - \alpha)^{-1} \sum_{s \in S} P_s \mathcal{C}_s \tag{15}$$

subject to

(1) *Selection of dynamic supply portfolio*: (7)–(11)
(2) *Risk constraints*:

(a) the tail cost for scenario s is defined as the nonnegative amount by which cost per part in scenario s exceeds VaR^c,

$$\begin{aligned}\mathcal{C}_s \geq &\sum_{i\in I} e_i u_i/D + \sum_{i\in I}\sum_{j\in J}\sum_{t\in T} o_{ij} d_j v_{ijt}/D \\ &+ \sum_{i\in I_s}\sum_{t\in T}\sum_{j\in J:\delta_j<t+\tau_{is}} (g_j(t+\tau_{is}-\delta_j)-\epsilon_{ij}) d_j v_{ijt}/D \\ &+ \sum_{i\notin I_s}\sum_{j\in J}\sum_{t\in T}(h_j - o_{ij}) d_j v_{ijt}/D - VaR^c \end{aligned} \qquad (16)$$

(3) *Non-negativity and integrality conditions*: (12), (13) and

$$\mathcal{C}_s \geq 0;\ \ s \in S. \qquad (17)$$

DSP_CV(sl): *Risk-averse selection of dynamic supply portfolio to maximise CVaR of service level*

Maximise

$$CVaR^{sl} = VaR^{sl} - (1-\alpha)^{-1}\sum_{s\in S} P_s \mathcal{S}_s \qquad (18)$$

subject to

(1) *Selection of supply portfolio*: (7)–(11)
(2) *Risk constraints*:

(a) the tail service level for scenario s is defined as the nonnegative amount by which VaR^{sl} exceeds service level in scenario s,

$$\mathcal{S}_s \geq VaR^{sl} - \sum_{i\in I_s}\sum_{j\in J}\sum_{t\in T:\underline{\delta}_j\leq t+\tau_{is}\leq \delta_j} d_j v_{ijt}/D;\ \ s \in S \qquad (19)$$

(3) *Non-negativity and integrality conditions*: (12), (13) and

$$\mathcal{S}_s \geq 0;\ \ s \in S. \qquad (20)$$

Note that variables VaR^c and VaR^{sl} do not need to be constrained of being nonnegative. As $\mathcal{C}_s$ and $\mathcal{S}_s$ are constrained of being positive, the model tries to decrease VaR^c and increase VaR^{sl}, respectively, and hence positively impact the objective function. However, large reduction in VaR^c and increase in VaR^{sl} may result in more scenarios with positive tail costs and service levels, respectively.

5. Computational examples

In this section, some computational examples are presented to illustrate possible applications of the proposed stochastic MIP models for selection of a dynamic supply portfolio in the presence of both delay and disruption risks. The problem is rarely considered in the literature and to the best of our knowledge there is no solution algorithm or benchmark problem that can be used for comparison of the proposed portfolio approach and MIP models. Although the input data for the examples are hypothetical, their relations to each other are real and in part they have been taken from real case studies (Sawik 2011a). In the cost-oriented supplier selection, a combination of disruption and delay risks directly impacts both shortage and delay penalties, while in the service-oriented decisions both demand fulfilment rate (the fraction of demand for parts fulfilled during the planning horizon) and service level (the fraction of demand for parts fulfilled within due windows) are simultaneously impacted. Therefore, the solution values of service level are reported along with the associated demand fulfilment rates, in particular for the service-oriented models, Furthermore, to emphasise the impact of supply delays on selection of a dynamic supply portfolio under combined disruption and delay risks, selected solutions with neglected delay penalties are reported for a comparison.

The following parameters have been used for the example problems:

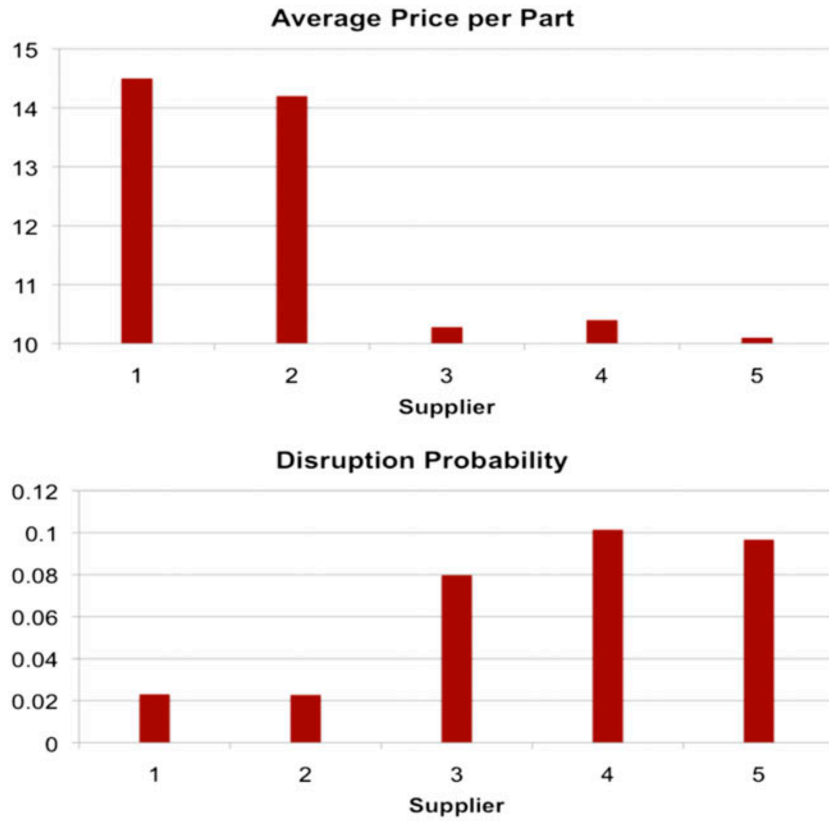

Figure 1. Suppliers characteristics.

- $\overline{I}$, the number of suppliers, was equal to 5.
- $\overline{R}$, the number of geographic regions, was equal to 2, and the subsets of suppliers were $I^1 = \{1, 2\}$ and $I^2 = \{3, 4, 5\}$, respectively.
- $\overline{J}$, the number of customer orders, was equal to 50.
- $\overline{T}$, the planning horizon, was equal to 14 periods.
- $\overline{\tau}$, maximum delivery delay was equal to 4 periods for each supplier, so that the set of all possible delays is $\mathcal{T} = \{0, 1, 2, 3, 4, 5\}$, where a dummy delay, $\overline{\tau} + 1 = 5$, represents local disruption of a supplier. The corresponding number of delivery scenarios, was equal to $\overline{S} = 6^{\overline{I}} = 7776$.
- d_j, the numbers of required parts for each customer order, were integers uniformly distributed over [500, 5000] for all customer orders j and the resulting total demand for parts was $D = 138000$.
- e_i, the cost of ordering parts, were integers in {8000, 9000} and {12000, 13000, 14000}, respectively for suppliers $i \in I^1$ and $i \in I^2$.
- o_{ij}, the unit price of parts for customer order j purchased from supplier i, was uniformly distributed over [13,15] and [9,11], respectively for suppliers $i \in I^1$ and $i \in I^2$.
- ϵ_{ij}=0.05o_{ij}, per unit price reduction for each delayed part of customer order j from supplier i was 5% of the unit price.
- $g_j = 1$, per unit and per period delay penalty cost was equal to 1 for all customer orders j.
- $h_j = 5\max_{i \in I}(o_{ij})$, per unit shortage cost for each customer order j, was equal to five times of the maximum purchasing cost of required parts.
- $c_{it} = 10000$;
- p_{i5}, the local disruption probability (dummy delay, $\overline{\tau} + 1 = 5$, represents local disruption) was uniformly distributed over [0.01,0.05] and [0.05;0.10], respectively, for suppliers $i \in I^1$ and $i \in I^2$, i.e. the disruption probabilities were drawn independently from U[0.01,0.05] and U[0.05;0.10], respectively.

  Given local disruption probabilities, p_{i5}, $i \in I$, the probabilities for different delay length $\tau = 0, 1, 2, 3, 4$ were calculated as follows:

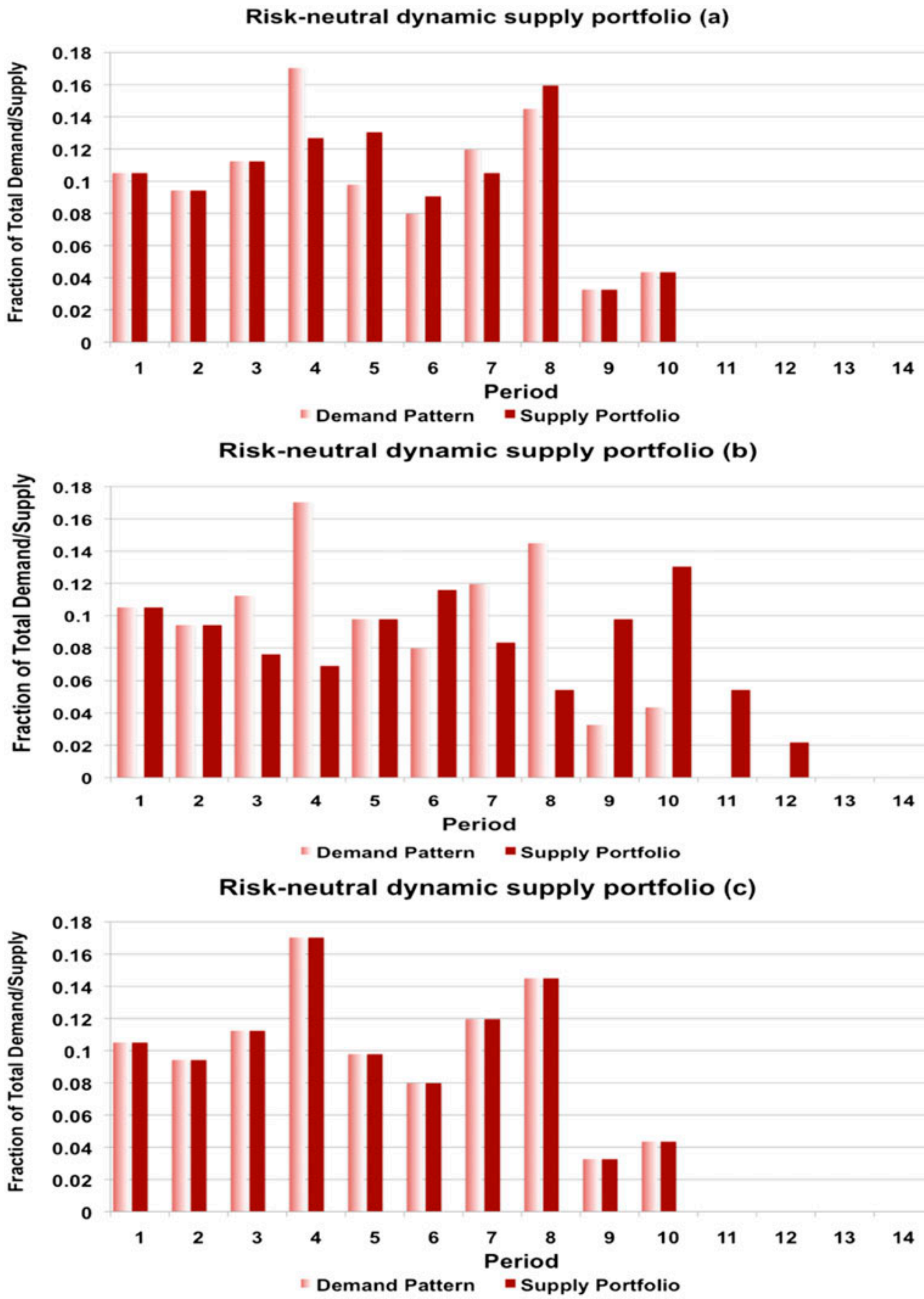

Figure 2. Risk-neutral dynamic supply portfolio: (a) model **DSP_E(c)**, (b) model **DSP_E(c)** with delay penalty neglected, (c) model **DSP_E(sl)**.

probability of on time delivery ($\tau = 0$), $p_{i0} = 0.3(1 - p_{i5})$;
probability of 1-period delay ($\tau = 1$), $p_{i1} = 0.25(1 - p_{i5})$;
probability of 2-period delay ($\tau = 2$), $p_{i2} = 0.2(1 - p_{i5})$;
probability of 3-period delay ($\tau = 3$), $p_{i3} = 0.15(1 - p_{i5})$;
probability of maximum, 4-period delay ($\tau = \overline{\tau} = 4$), $p_{i4} = 0.1(1 - p_{i5})$;
for all suppliers $i \in I$, i.e. the longer delay the lower probability of its occurrence.

Table 3. Risk-neutral solutions.

Model **DSP_E(c)**	Model **DSP_E(c)**[(a)]	Model **DSP_E(sl)**
Var. = 3505, Bin. = 3505, Cons. = 3675, Nonz. = 18325 [(b)]		
$E^c = 15.47$, (3.73[(c)], 0.36[(d)])	$E^c = 15.85$, (4.46[(c)], 0.88[(d)])	$E^{sl} = 73.08\%$
$E^{sl} = 69.91\%$	$E^{sl} = 48.73\%$	$E^c = 16.04$, (1.89[(c)] 0.34[(d)])
94.93 [(e)]	93.96 [(e)]	97.44 [(e)]
15.47[(f)]	15.23[(f)]	73.11[(f)]
Suppliers Selected (% of total demand)[(g)]		
1(14)		1(32)
2(37)	2(34)	2(63)
3(49)	3(66)	3(5)

(a) model **DSP_E(c)** without delay penalty, $\sum_{s\in S}\sum_{i\in I_s}\sum_{t\in T}\sum_{j\in J:\delta_j<t+\tau_{is}} P_s(g_j(t+\tau_{is}-\delta_j)-\epsilon_{ij})d_j v_{ijt}/D$, in (5).

(b) Var. = total number of variables, Bin. = number of binary variables, Cons. = number of constraints, Nonz. = number of nonzero coefficients.

(c) $\sum_{s\in S}\sum_{i\notin I_s}\sum_{j\in J}\sum_{t\in T} P_s(h_j-o_{ij})d_j v_{ijt}/D$ - shortage penalty.

(d) $\sum_{s\in S}\sum_{i\in I_s}\sum_{t\in T}\sum_{j\in J:\delta_j<t+\tau_{is}} P_s(g_j(t+\tau_{is}-\delta_j))d_j v_{ijt}/D$ - delay penalty.

(e) $\sum_{s\in S}\sum_{i\in I_s}\sum_{j\in J}\sum_{t\in T} P_s d_j v_{ijt}/D \times 100\%$ - expected fulfilment rate.

(f) LP relaxation solution value of the objective function.

(g) $1(\sum_{j\in J}\sum_{t\in T} d_j v_{1jt}/D \times 100\%)$,
$2(\sum_{j\in J}\sum_{t\in T} d_j v_{2jt}/D \times 100\%)$,
$3(\sum_{j\in J}\sum_{t\in T} d_j v_{3jt}/D \times 100\%)$.

Notice that for each supplier i, the expected delay is equal to 2 periods ($\lceil 0.25(1-p_{i5})+2(0.2(1-p_{i5}))+3(0.15(1-p_{i5}))+4(0.1(1-p_{i5}))/(1-p_{i5})\rceil$=2)

- p^r, the regional disruption probability was 0.005 and 0.01, respectively for region $r=1$ and $r=2$.
- δ_j, the latest delivery date of parts required for customer order j, was integer uniformly distributed over [3, $\overline{T}$], i.e. generated from a U[3;14] distribution.
- $\underline{\delta}_j = \delta_j - 2$, the earliest delivery date of parts required for each customer order j, was two periods earlier (i.e. the expected delay) than the latest delivery date.
- ρ_i, the expected defect rate of each supplier i was exponentially distributed.
- α, the confidence level, was equal to 0.50, 0.75, 0.90, 0.95 or 0.99.

Note that cost of lost customer orders, h_j, is set to be much higher than the corresponding cost, g_j, of delayed orders, which is typical for industrial practice.

Figure 1 shows basic characteristics of each supplier i, average price per part, $\sum_{j\in J} o_{ij}/\overline{J}$, and disruption probability, π_i, (3). Suppliers $i=1,2$ in region $r=1$ are most reliable and most expensive, supplier $i=4$ is most unreliable, while supplier $i=5$ is the cheapest one.

The risk-neutral solutions for models **DSP_E(c)** and **DSP_E(sl)** are shown in Table 3, and the risk-averse solutions for models **DSP_CV(c)** and **DSP_CV(sl)** with different confidence levels, in Table 4. For each model Table 3 shows the associated values of both risk-neutral objective functions, expected cost, E^c, and expected service levels, E^{sl}. Moreover, for model **DSP_E(c)**, the shortage and delay penalties are separately indicated. In Table 4, conditional cost-at-risk, CVaR^c, and conditional service-at-risk, CVaR^{sl}, are shown along with the associated expected cost, E^c, and expected service level, E^c.

Table 3 indicates that the risk-neutral supply portfolios do not include the most unreliable suppliers $i=4,5$. The corresponding risk-neutral dynamic supply portfolios, $(\sum_{i\in I}\sum_{j\in J} d_j v_{ijt}/D,\ t\in T)$, are shown in Figure 2 for cost-oriented and service-oriented objectives. For comparison, demand pattern, $(\sum_{j\in J:\underline{\delta}_j=t} d_j/D,\ t\in T)$, is also presented. Both dynamic portfolios follow the demand pattern, in particular the service-oriented portfolio, see Figure 2(c). In addition, Figure 2(b) shows cost-oriented dynamic supply portfolio with neglected delay penalty,

$\sum_{s\in S}\sum_{i\in I_s}\sum_{t\in T}\sum_{j\in J:\delta_j<t+\tau_{is}} P_s(g_j(t+\tau_{is}-\delta_j))d_j v_{ijt}/D$, in the objective function (5). Comparison of Figure 2(a) and (b), clearly indicate that the dynamic supply portfolio with no delay risk considered is more unleveled, and leads to greater supply fluctuations and manufacturing delays. Table 3 shows that the most reliable supplier 1 is not selected when delay risk is disregarded.

Table 4. Risk-averse solutions.

Confidence level α	0.50	0.75	0.90	0.95	0.99
Model **DSP_CV(c)**					
Var. = 11282, Bin. = 3505, Cons. = 11451, Nonz. = 27288757 [a]					
CVaR^c	17.29	20.24	28.41	35.82	45.59
VaR^c	14.19	14.38	14.87	30.04	43.07
E^c	15.74	15.75	15.75	15.80	15.68
E^{sl}%	71.80	72.36	72.36	71.10	70.47
Expected fulfillment rate[b]	97.71	97.71	97.71	94.88	94.58
LP [c]	17.27	20.19	28.29	35.74	45.47
Suppliers selected (% of total demand)[d]	1(41)	1(43)	1(49)	1(30)	1(27)
	2(59)	2(57)	2(51)	2(29)	2(25)
				3(14)	3(24)
				4(14)	
				5(13)	5(24)
Model **DSP_CV(sl)**					
Var. = 11282, Bin. = 3505, Cons. = 11451, Nonz. = 22713877 [a]					
CVaR^{sl}%	53.97	43.87	32.66	25.46	13.99
VaR^{sl}%	71.74	59.78	39.85	39.85	19.93
E^{sl}%	71.02	70.16	70.16	70.16	70.14
Expected fulfillment rate[b]	94.70	93.54	93.54	93.54	93.52
E^c	16.42	16.68	16.68	16.47	16.78
LP [c]	53.97	43.93	32.75	25.49	14.04
Suppliers selected (% of total demand)[d]	1(28)	1(20)			
	2(28)	2(20)			
	3(15)	3(20)			
	4(14)	4(20)			
	5(15)	5(20)			

[a] Var. = total number of variables, Bin. = number of binary variables, Cons. = number of constraints, Nonz. = number of nonzero coefficients.
[b] $\sum_{s\in S}\sum_{i\in I_s}\sum_{j\in J}\sum_{t\in T} P_s d_j v_{ijt}/D \times 100\%$.
[c] LP relaxation solution value of the objective function.
[d] $1(\sum_{j\in J}\sum_{t\in T} d_j v_{1jt}/D \times 100\%)$,
$2(\sum_{j\in J}\sum_{t\in T} d_j v_{2jt}/D \times 100\%)$,
$3(\sum_{j\in J}\sum_{t\in T} d_j v_{3jt}/D \times 100\%)$,
$4(\sum_{j\in J}\sum_{t\in T} d_j v_{4jt}/D \times 100\%)$,
$5(\sum_{j\in J}\sum_{t\in T} d_j v_{5jt}/D \times 100\%)$.

In the computational experiments for the risk-averse portfolios, the confidence level α is set at five levels of 0.5, 0.75, 0.90, 0.95 and 0.99, which means that focus is on minimising the highest 50%, 25%, 10%, 5%, and 1% of all scenario outcomes, i.e. costs per part or service level. When α increases, a more risk-aversive decision-making focuses on a smaller set of outcomes and the number of selected suppliers also is increasing to mitigate the impact of disruptions risks by diversification of the supply portfolio.

Table 4 demonstrates that for model **DSP_CV(c)** and low confidence levels, $\alpha = 0.5, 0.75, 0.9$, only the most reliable suppliers 1 and 2 are selected to minimise the dominating worst-case shortage cost. However, for a larger α, these suppliers are supported by the less reliable suppliers 3, 4 and 5 to better mitigate the impact of part shortages by a more diversified portfolio.

For model **DSP_CV(sl)**, the total demand is equally allotted among all suppliers to better mitigate the impact of disruption risks on worst-case service level. Note that for the lowest confidence level α, VaR^c is smaller than expected cost, E^c, and VaR^{sl} is greater than expected service level, E^{sl}.

The cost-oriented risk-averse dynamic supply portfolios for the lowest and highest confidence levels, respectively, $\alpha = 0.5$ and $\alpha = 0.99$, are shown in Figure 3. For comparison, Figure 3 also shows the risk-averse dynamic supply portfolio with no

Table 5. Solution results for different shortage-to-delay unit penalty ratio.

Unit penalty ratio, h/g	1	10	25	50	75	100
			Model **DSP_E(c)**			
E^c	9.35	10.20	11.55	13.80	15.54	16.33
E^{sl}%	66.57	66.74	67.04	66.40	70.56	71.23
Expected fulfillment rate[(a)]	90.51	90.57	90.97	91.11	95.08	97.71
LP [(b)]	9.33	10.19	11.55	13.77	15.53	16.32
Suppliers selected (% of total demand)[(c)]					1(14)	1(40)
					2(40)	2(60)
	3(23)	3(25)	3(44)	3(51)	3(46)	
	4(42)	4(39)	4(21)	4(18)		
	5(35)	5(36)	5(35)	5(31)		
			Model **DSP_CV(c)** with $\alpha = 0.99$			
CVaR^c	11.10	11.13	19.61	32.85	46.17	59.72
VaR^c	11.00	11.00	18.85	31.27	43.76	56.26
E^c	9.36	10.20	13.22	14.38	15.73	17.10
E^{sl}%	66.86	66.86	70.60	70.78	70.72	70.69
Expected fulfillment rate[(a)]	90.73	90.73	94.85	94.64	94.56	94.52
LP [(b)]	11.08	11.10	19.40	32.75	46.27	59.60
Suppliers selected (% of total demand)[(c)]			1(27)	1(27)	1(26)	1(26)
			2(30)	2(26)	2(26)	2(25)
	3(34)	3(33)	3(17)	3(24)	3(24)	3(25)
	4(34)	4(34)	4(9)			
	5(32)	5(33)	5(17)	5(23)	5(24)	5(24)

(a) $\sum_{s\in S}\sum_{i\in I_s}\sum_{j\in J}\sum_{t\in T} P_s d_j v_{ijt}/D \times 100\%$.
(b) LP relaxation solution value of the objective function.
(c) $1(\sum_{j\in J}\sum_{t\in T} d_j v_{1jt}/D \times 100\%)$,
$2(\sum_{j\in J}\sum_{t\in T} d_j v_{2jt}/D \times 100\%)$,
$3(\sum_{j\in J}\sum_{t\in T} d_j v_{3jt}/D \times 100\%)$,
$4(\sum_{j\in J}\sum_{t\in T} d_j v_{4jt}/D \times 100\%)$,
$5(\sum_{j\in J}\sum_{t\in T} d_j v_{5jt}/D \times 100\%)$.

delay penalty, $\sum_{i\in I_s}\sum_{t\in T}\sum_{j\in J:\delta_j<t+\tau_{is}}(g_j(t+\tau_{is}-\delta_j))d_j v_{ijt}/D$, in the risk constraints (16). While for the risk-averse dynamic portfolio the same suppliers are selected, the allocation of orders among suppliers and over time is different when delay risk is disregarded. For example, for $\alpha = 0.5$, the percentage of demand allocation is changing from (Supplier 1: 41%, Supplier 2: 59%, see Table 4) to (Supplier 1: 25%, Supplier 2: 75%), that is more demand is moved to the cheaper supplier 2. The results clearly indicate that when delay risk is neglected, the dynamic portfolios are spread over more periods and may lead to greater manufacturing delays. Thus, neglecting potential delay risks might negatively impact material supplies.

In addition to expected service level, E^{sl}, Tables 3 and 4 show the associated expected fraction of fulfilled demand (on-time or delayed), $\sum_{s\in S}\sum_{i\in I_s}\sum_{j\in J}\sum_{t\in T} P_s d_j v_{ijt}/D$. Comparison of the latter solution values with E^{sl}, clearly indicates that a large fraction of fulfilled demand is delayed. For all models the expected fractions of fulfilled demand are very similar and close to 95%. A high expected fulfilment rate indicates that the dynamic supply portfolios well mitigate the impact of disruption risks. The expected service levels are similar (close to 70%) only for model **DSP_CV(sl)**. For the cost-oriented models, however, E^{sl} depends on the confidence level, α, for model **DSP_CV(c)** and attains its lower value (48.73%) for model **DSP_E(c)** with neglected delay penalty in the objective function.

In order to provide more insights, additional computational experiments were conducted with different shortage-to-delay unit penalty ratios: for unit delay penalty, $g_j = g = 1,\ \forall j \in J$, and unit shortage penalty, $h_j = h \in \{1, 10, 25, 50, 75, 100\}$, $\forall j \in J$. For different unit penalty ratio, h/g, Table 5 presents risk-neutral solutions for model **DSP_E(c)** and risk-averse solutions for model **DSP_CV(c)** with the highest confidence level $\alpha = 0.99$.

For the risk-neutral decision-making, the solution results are in line with an intuitive point of view. As shortage-to-delay unit penalty ratio increases, more demand is moved from unreliable, low-cost suppliers to reliable, high-cost suppliers to

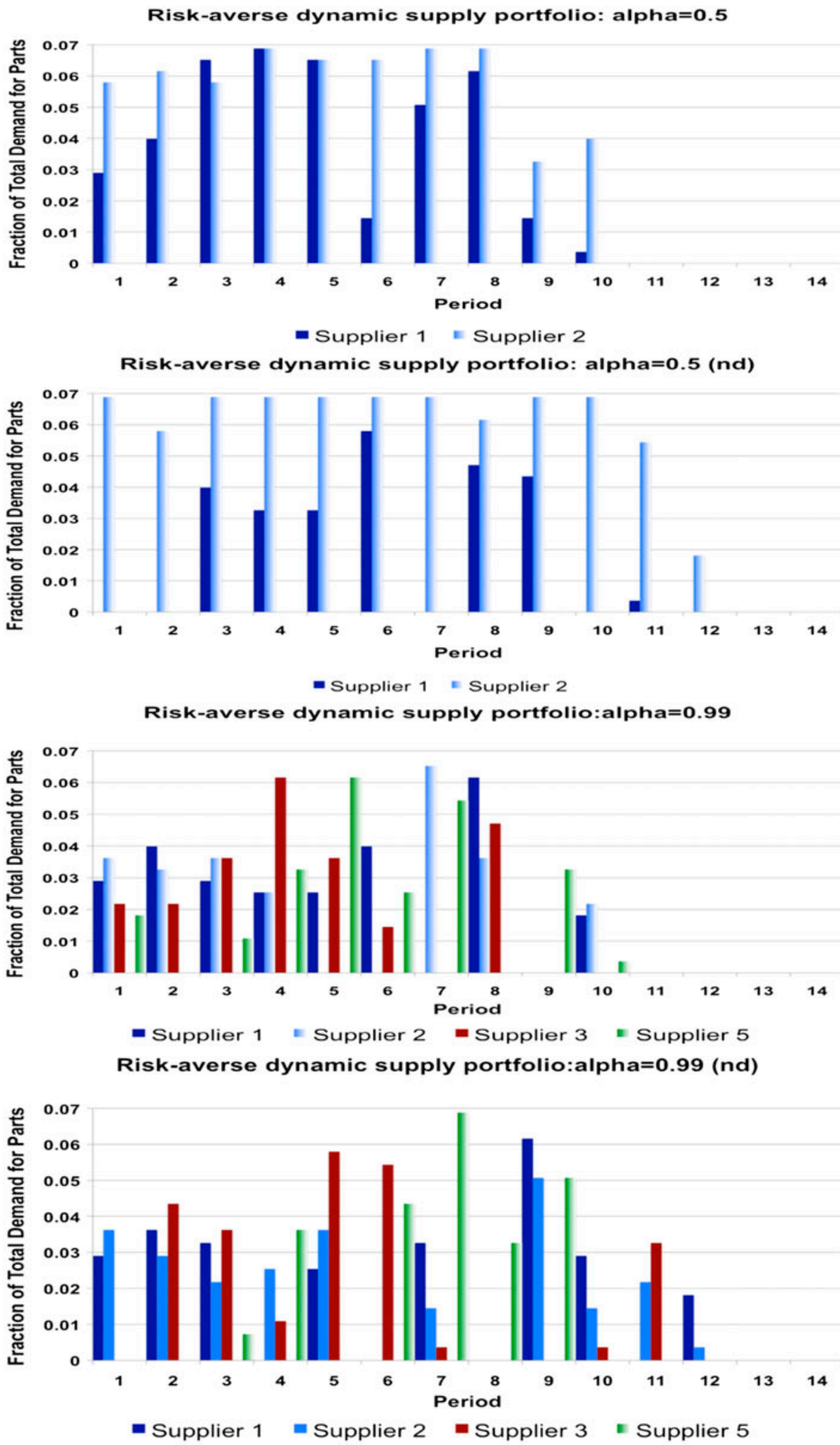

Figure 3. Risk-averse dynamic supply portfolio for model **DSP_CV(c)**: $\alpha = 0.5$ and $\alpha = 0.99$ (nd - neglected delay penalty).

Table 6. Risk-neutral solutions for LDN scenarios.

Model **DSP_E(c)**	Model **DSP_E(sl)**
Var. = 3505, Bin. = 3505, Cons. = 3675, Nonz. = 18325 [(a)]	
$E^c = 16.64$	$E^{sl} = 97.71\%$ [(b)]
$E^{sl} = 94.99\%$ [(b)]	$E^c = 18.02$
16.62[(c)]	97.71[(c)]
Suppliers Selected (% of total demand)[(d)]	
1(11)	1(26)
2(41)	2(74)
3(48)	

[(a)] Var. = total number of variables, Bin. = number of binary variables, Cons. = number of constraints, Nonz. = number of nonzero coefficients.
[(b)] $\sum_{s \in S} \sum_{i \in I_s} \sum_{j \in J} \sum_{t \in T} P_s d_j v_{ijt} / D \times 100\%$ - expected fulfilment rate.
[(c)] LP relaxation solution value of the objective function.
[(d)] $1(\sum_{j \in J} \sum_{t \in T} d_j v_{1jt} / D \times 100\%)$,
$2(\sum_{j \in J} \sum_{t \in T} d_j v_{2jt} / D \times 100\%)$,
$3(\sum_{j \in J} \sum_{t \in T} d_j v_{3jt} / D \times 100\%)$.

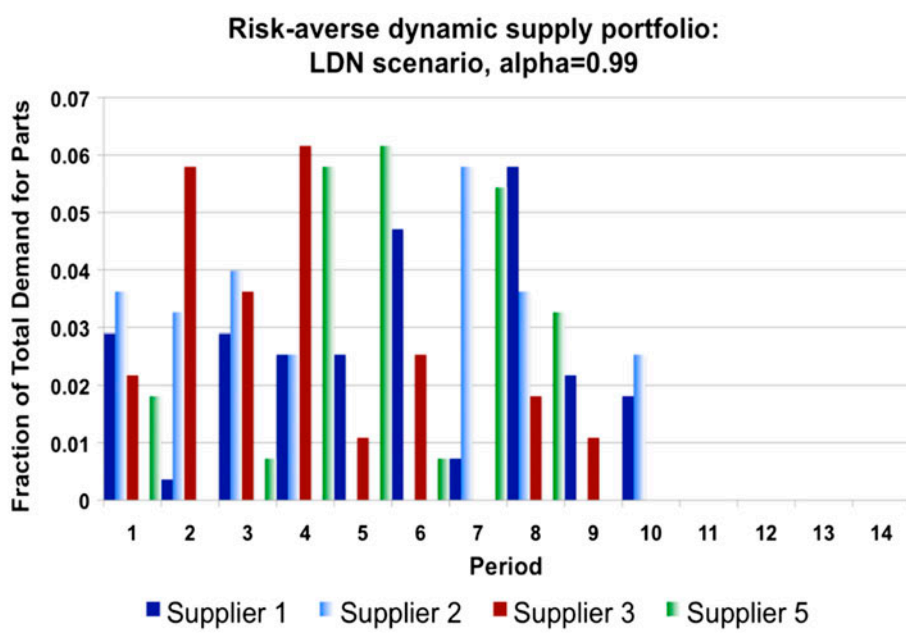

Figure 4. Risk-averse dynamic supply portfolios for model **DSP_CV(c)** and LDN scenario.

minimise shortage cost. For a low ratio, the risk-neutral supply portfolio does not include the most reliable and most expensive suppliers 1 and 2 to minimise the dominating purchasing costs, whereas for a high ratio, the most reliable suppliers 1 and 2 are selected only to minimise the dominating shortage costs. For the risk-averse decision-making, the supply portfolio for low unit penalty ratios also does not include the most reliable and most expensive suppliers 1 and 2, however for higher ratios, these suppliers are selected along with the less reliable supporting suppliers to better mitigate the impact of shortage risk by portfolio diversification. Except for the most unreliable supplier 4, which is not selected at all for all higher ratios, $h/g = 50, 75, 100$.

The results shown in Tables 3–5 clearly indicate that the proposed time-indexed stochastic MIP models have strong LP relaxations.

Table 7. Risk-averse solutions for LDN scenarios.

Confidence level α	0.50	0.75	0.90	0.95	0.99
Model **DSP_CV(c)**					
Var. = 3538, Bin. = 3505, Cons. = 3739, Nonz. = 186613 [(a)]					
CVaR^c	18.21	20.88	28.89	36.53	46.01
VaR^c		15.54		30.99	43.73
E^c		16.87		16.95	16.83
Expected fulfilment rate[(b)]		97.71		94.85	94.56
LP [(c)]	18.19	20.86	28.87	36.44	45.96
Suppliers selected (% of total demand)[(d)]		1(43)		1(30)	1(26)
		2(57)		2(29)	2(26)
				3(13)	3(24)
				4(14)	
				5(14)	5(24)
Model **DSP_CV(sl)**					
Var. = 3538, Bin. = 3505, Cons. = 3707, Nonz. = 74389 [(a)]					
CVaR%	95.43	90.86	77.14	62.26	46.23
VaR%	100	100	100	71.38	50
Expected fulfilment rate[(b)]	97.71	97.71	97.71	94.73	94.44
E^c	17.97	18.11	18.00	19.08	18.27
LP [(c)]	95.43	90.86	77.14	62.27	46.23
Suppliers selected (% of total demand)[(d)]	1(25)	1(28)	1(26)	1(29)	1(25)
	2(75)	2(72)	2(74)	2(29)	2(25)
				3(14)	3(25)
				4(14)	
				5(14)	5(25)

[(a)] Var. = total number of variables, Bin. = number of binary variables,
Cons. = number of constraints, Nonz. = number of nonzero coefficients.
[(b)] $\sum_{s\in S}\sum_{i\in I_s}\sum_{j\in J}\sum_{t\in T} P_s d_j v_{ijt}/D \times 100\%$.
[(c)] LP relaxation solution value of the objective function.
[(d)] $1(\sum_{j\in J}\sum_{t\in T} d_j v_{1jt}/D \times 100\%)$,
$2(\sum_{j\in J}\sum_{t\in T} d_j v_{2jt}/D \times 100\%)$,
$3(\sum_{j\in J}\sum_{t\in T} d_j v_{3jt}/D \times 100\%)$,
$4(\sum_{j\in J}\sum_{t\in T} d_j v_{4jt}/D \times 100\%)$,
$5(\sum_{j\in J}\sum_{t\in T} d_j v_{5jt}/D \times 100\%)$.

5.1 *Worst-case scenarios with longest delays and disruptions*

In this subsection, a special subset of delivery scenarios is considered such that delivery of parts from each supplier is either delayed by maximum delay length, $\overline{\tau}$, or parts are not delivered at all, because of supply disruptions. Let us call such binomial delivery scenarios, LDN (Longest Delay-or-Never) scenarios. The total number of LDN scenarios is $2^{\overline{I}} = 32$. Given local disruption probabilities, $p_{i5},\ i \in I$, the probability for the longest delay of delivery is simply $p_{i4} = (1 - p_{i5})$, while the remaining probabilities, $p_{i0}, p_{i1}, p_{i2}, p_{i3}$ are zero for all $i \in I$. Notice that binomial LDN delivery scenarios can be considered as pure all-or-nothing disruption scenarios, where ordered parts are either delivered with a fixed delay, $\overline{\tau}$, or not delivered at all.

For LDN scenarios the fraction of demand fulfilled within delivery due windows is always zero because the longest delay, $\overline{\tau} = 4$, is always greater than each due window length, $\overline{\delta}_j - \underline{\delta}_j = 2,\ j \in J$. Therefore, in this subsection the service level is measured by demand fulfilment rate, i.e. the fraction of demand fulfilled during the planning horizon.

Equation (6) is replaced by

$$E^{sl} = \sum_{s\in S}\sum_{i\in I_s}\sum_{j\in J}\sum_{t\in T} P_s d_j v_{ijt}/D,$$

Table 8. Probability of cost per part for model **DSP_CV(c)**: LDN scenarios.

Cost interval	$\alpha = 0.5, 0.75, 0.9$	$\alpha = 0.95$	$\alpha = 0.99$
[13, 14]	0	0.731265	0.805646
[15, 16]	0.959466	0	0
[22, 23]	0	0.199973	0
[28, 29]	0	0	0.167932
[30, 31)	0	0.037792	0
[31, 32]	0	0.007137	0
[39, 40)	0	0.017474	0
[40, 41]	0.017756	0	0
[43, 44]	0	0	0.025001
[48, 49)	0	0.004721	0
[49, 50]	0.017455	0	0
[56, 57]	0	0.001481	0
[58, 59]	0	0	0.001335
[65, 66]	0	0.000100	0
[73, 74]	0.005323	0	0

Table 9. Probability of fulfilment rate for model **DSP_CV(sl)**: LDN scenarios.

Fulfillment rate interval %	$\alpha = 0.5, 0.75, 0.9$	$\alpha = 0.95$	$\alpha = 0.99$
[14, 15]	0	0.000101	0
[24, 25)	0	0	0.001335
[25, 26)	0.017455	0	0
[26, 27]	0	0.017455	0
[28, 29]	0	0.001481	0
[42, 43)	0	0.004459	0
[43, 44]	0	0.000262	0
[49, 50]	0	0	0.025001
[56, 57)	0	0.002034	0
[57, 58]	0	0.015440	0
[71, 72]	0	0.044929	0
[73, 74)	0	0.017756	0
[74, 75)	017756	0	0
[75, 76]	0	0	0.167932
[85, 86]	0	0.199973	0
[99, 100]	0.959466	0.731265	0.805646

and risk constraints (19) by

$$\mathcal{S}_s \geq VaR^{sl} - \sum_{i \in I_s} \sum_{j \in J} \sum_{t \in T} d_j v_{ijt}/D; \;\; s \in S.$$

The risk-neutral solutions for LDN scenarios and models **DSP_E(c)** and **DSP_E(sl)** are summarised in Table 6. The solution results for model **DSP_E(c)** are similar to the corresponding results for the general delivery scenarios, since demand fulfilment rate is independent of delivery delays. Table 6 shows that the expected costs are greater for LDN scenarios (cf. Table 3).

The risk-averse solutions for LDN scenarios are summarised in Table 7. Table 7 demonstrates that for both models **DSP_CV(c)** and **DSP_CV(sl)**and low confidence levels the two most reliable and expensive suppliers 1 and 2 are selected only, while for a greater α the portfolio is more diversified. Suppliers 1 and 2 are supported by the less reliable suppliers 3, 4 and 5 to better mitigate the impact of disruption risk and minimise the worst-case cost or maximise the worst-case fulfilment rate. The results indicate that in the example problems the shortage costs are predominating worst-case costs.

Table 7 also shows that solution values for model **DSP_CV(c)** and binomial LDN delivery scenarios are greater than the corresponding values for the general multinomial delivery scenario, while the corresponding supply portfolios are similar

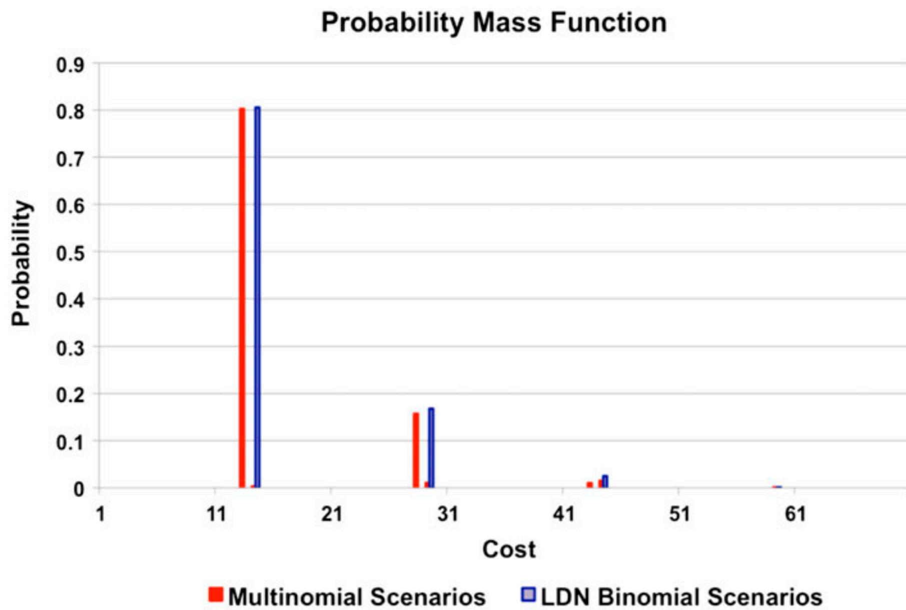

Figure 5. Probability mass function for model **DSP_CV(c)** and $\alpha = 0.99$: multinomial vs. binomial scenarios.

(cf. Table 4). An example of optimal risk-averse dynamic supply portfolio for model **DSP_CV(c)** and the highest confidence level $\alpha = 0.99$ is presented in Figure 4. Despite nearly equal allocation of total demand for parts among four suppliers (cf. Table 7), the order allocation over the planning horizon is unbalanced to better meet the varying customer demand pattern (cf. Figure 3)

For optimal risk-averse supply portfolios and LDN scenarios, Tables 8 and 9 present discrete distributions of cost per part and demand fulfilment rate, respectively. The tables show corresponding probabilities concentrated at each level of cost and fulfilment rate. The probabilities are concentrated at a few points only, which is typical for the scenario-based optimisation under uncertainty, where the probability measure is concentrated in finitely many points.

The cost distributions for optimal risk-averse supply portfolio and the highest confidence level $\alpha = 0.99$, for worst-case LDN binomial disruption scenarios and general multinomial delivery scenarios are compared in Figure 5. For the worst-case LDN binomial scenarios the probability measure is concentrated in a smaller number of points than for the general multinomial scenarios and contains larger probability atoms at higher costs. This indicates that the impact of LDN binomial scenarios is more difficult to mitigate than that of general multinomial delay and disruption scenarios.

The computational experiments were performed using the AMPL programming language and the Gurobi 7.0.0 solver on a MacBookPro laptop with Intel Core i7 processor running at 2.8GHz and with 16GB RAM. The solver was capable of finding proven optimal solutions for all examples with CPU time ranging from fraction of a second for risk-neutral solutions to a few minutes for risk-averse solutions.

6. Conclusion

The problem of selection a multi-period supply portfolio under combined delay and disruption risks has been considered. A combination of the low probability and high impact supply disruptions with the high probability and low impact supply delays and, in addition, the combination of local delay risks with local and regional disruption risks contribute to the problem complexity. Using the portfolio approach, however, the resulting stochastic combinatorial optimisation problem has been transformed to the scenario-based stochastic mixed integer program, which can be easily solved using commercially available MIP solvers.

The computational results indicate that:

- the portfolio approach leads to a time-indexed stochastic MIP formulation with a strong LP relaxation, which has proven to be computationally very efficient;
- both cost- and service-oriented dynamic supply portfolios that simultaneously mitigate the impact of low-probability disruption risk and high-probability delay risk lead to a high expected demand fulfilment rate;

- neglecting potential delay risks in supplier selection may lead to greater supply fluctuations and manufacturing delays, which is particularly harmful in a make-to-order and just-in-time environment: when the delay risk is disregarded the most reliable suppliers are not selected or are allotted less demand and the dynamic portfolio is spread over more periods;
- for the risk-neutral decision-making as shortage-to-delay unit penalty ratio increases, more demand is moved from unreliable, low-cost suppliers to reliable, high-cost suppliers to minimise expected shortage cost;
- for the risk-averse decision-making, the supply portfolio for a low shortage-to-delay unit penalty ratio does not include most reliable and expensive suppliers, whereas for the higher ratios these suppliers are selected along with the less reliable supporting suppliers to better mitigate the impact of shortage risk by portfolio diversification;
- for LDN scenarios the probability measure for optimal risk-averse dynamic portfolio is concentrated in a fewer number of points and contains larger probability atoms at higher costs.

In the future research various simplifying assumptions used in the proposed models can be relaxed. For example, the multiple deliveries from each supplier can be replaced by a single batch delivery, where different orders are batched together for delivery. Moreover, when suppliers rely on 3PL providers, a fixed pre-specified delivery date or delivery time window can also be considered. A direct enhancement of the developed models is a multiple part types setting with subsets of suppliers available for each part type. In a more general setting, the dynamic supply portfolio can be determined over a rolling horizon to account for a dynamic arrival of customer orders.

Acknowledgements

The author is grateful to two anonymous reviewers for providing many constructive comments which significantly helped to improve this paper.

Disclosure statement

No potential conflict of interest was reported by the author.

Funding

This work was supported by NCN research [grant number #DEC-2013/11/B/ST8/04458], and by AGH [grant number #11.11.200.324].

ORCID

Tadeusz Sawik http://orcid.org/0000-0002-6054-550X

References

Ahmadjian, C., and J. Lincoln. 2001. "Keiretsu, Governance, and Learning: Case Studies in Change from the Japanese Automotive Industry." *Organization Science* 12 (6): 683–701.

Aissaoui, N., M. Haouari, and E. Hassini. 2007. "Supplier Selection and Order lot Sizing Modeling: A Review." *Computers & Operations Research* 34: 3516–3540.

Aksoy, A., and N. Ozturk. 2011. "Supplier Selection and Performance Evaluation in Just-in-time Production Environments." *Expert Systems with Applications* 38: 6351–6359.

Berger, P. D., A. Gerstenfeld, and A. Z. Zeng. 2004. "How many Suppliers are Best? A Decision-analysis Approach. Omega: The." *International Journal of Management Science* 32 (1): 9–15.

Berger, P. D., and A. Z. Zeng. 2006. "Single vs. Multiple Sourcing in the Presence of Risks." *Journal of the Operational Research Society* 57 (3): 250–261.

Birge, J. R., and F. Louveaux. 2011. *Introduction to Stochastic Programming*. New York: Springer.

Chahar, K., and K. Taaffe. 2009. "Risk Averse Demand Selection with All-or-nothing Orders. Omega: The." *International Journal of Management Science* 37 (5): 996–1006.

Che, Z. H., and H. S. Wang. 2008. "Supplier Selection and Supply Quantity Allocation of Common and Non-common Parts with Multiple Criteria under Multiple Products." *Computers and Industrial Engineering* 55: 110–133.

Chen, Z. L. 2010. "Integrated Production and Outbound Distribution Scheduling: Review and Extensions." *Operations Research* 58 (1): 130–148.

Dupont, L., C. Bernard, F. Hamdi, and F. Masmoudi. 2017. "Supplier Selection under Risk of Delivery Failure: A Decision-support Model Considering Managers' Risk Sensitivity." *International Journal of Production Research*. doi:10.1080/00207543.2017.1364442.

Demirtas, E. A., and O. Ustun. 2008. “An Integrated Multiobjective Decision Making Process for Supplier Selection and Order Allocation. Omega: The.” *International Journal of Management Science* 36: 76–90.
Eden, C., T. M. Williams, F. Ackermann, and S. Howick. 2000. “On the Nature of dDisruption and Delay.” *Journal of the Operational Research Society* 51: 291–300.
Fattahi, M., K. Govindan, and E. Keyvanshokooh. 2017. “Responsive and Resilient Supply Chain Network Design under Operational and Disruption Risks with Delivery Lead-time Sensitive Customers.” *Transportation Research Part E* 101: 176–20.
Fujimoto, T., and Y. W. Park. 2013. “Balancing Supply Chain Competitiveness and Robustness Through "Virtual dual Sourcing": Lessons from the Great East Japan Earthquake.” *International Journal of Production Economics* 147: 429–436.
Gurnani, H., A. Mehrotra, and S. Ray, eds. 2012. *Supply Chain Disruptions: Theory and Practice of Managing Risk*. Springer: London.
Hammami, R., C. Temponi, and Y. Frein. 2014. “A Scenario-based Stochastic Model for Supplier Selection in Global Context with Multiple Buyers, Currency Fluctuation Uncertainties, and Price Discounts.” *European Journal of Operational Research* 233: 159–170.
Hamdi, F., A. Ghorbel, F. Masmoudi, and L. Dupont. 2015. “Optimization of a Supply Portfolio in the Context of Supply Chain Risk Management: Literature Review.” *Journal of Intelligent Manufacturing*. doi:10.1007/s10845-015-1128-3.
Ho, W., X. Xu, and P. K. Dey. 2010. “Multi-criteria Decision Making Approaches for Supplier Evaluation and Selection: A Literature Review.” *European Journal of Operational Research* 202: 16–24.
Kasilingam, R. G., and C. P. Lee. 1996. “Selection of Vendors: A Mixed-integer Programming Approach.” *Computers and Industrial Engineering* 31: 347–350.
Levner, E., and A. Ptuskin. 2017. “Entropy-based Model for the Ripple Effect: Managing Environmental Risks in Supply Chains.” *International Journal of Production Research*. doi:10.1080/00207543.2017.1374575.
Li, L., and Z. B. Zabinsky. 2011. “Incorporating Uncertainty into a Supplier Selection Problem.” *International Journal of Production Economics* 134: 344–356.
Manavazhi, M. R., and K. A. Dinesh. 2002. “Material and Equipment Procurement Delays in Highway Projects in Nepal.” *International Journal of Project Management* 20 (8): 627–632.
Marszewska, J. R. 2016. “2016. Implications of Seismic Hazard in Japan on Toyota Supply Chain Disruption Risks.” In *Proceedings of 13th International Conference on Industrial Logistics*, Zakopane, Poland, Sept 28 to Oct 1, 178–185.
Matsuo, H. 2015. “Implications of the Tohoku Earthquake for Toyota’s Coordination Mechanism: Supply Chain Disruption of Automotive Semiconductors.” *International Journal of Production Economics* 161: 217–227.
Meena, P. L., S. P. Sarmah, and A. Sarkar. 2014. “Sourcing Decisions under Risks of Catastrophic Event Disruptions.” *Transportation Research Part E* 47: 1058–1074.
Mizgier, K. J., S. M. Wagner, and P. J. Matthias. 2015. “Disentangling Diversification in Supply Chain Networks.” *International Journal of Production Economics* 162: 115–124.
Namdar, J., X. Li, R. Sawhney, and N. Pradhan. 2017. “Supply Chain Resilience for Single and Multiple Sourcing in the Presence of Disruption Risks.” *International Journal of Production Research*. doi:10.1080/00207543.2017.1370149.
Parlar, M., and D. Perry. 1996. “Inventory Models of Future Supply Uncertainty with Single and Multiple Suppliers. em.” *Naval Research Logistics* 43: 191–210.
Park, Y., P. Hong, and J. J. Roh. 2013. “Supply Chain Lessons from the Catastrophic Natural Disaster in Japan.” *Business Horizon* 56 (1): 75–85.
Quang, H. T., and Y. Hara. 2017. “Risks and Performance in Supply Chain: The Push Effect.” *International Journal of Production Research*. doi:10.1080/00207543.2017.1363429.
Rabbani, M., S. H. Khalili, H. Janani, and M. Shiripour. 2014. “Optimization of a Dynamic Supply Portfolio Considering Risks and Discounts Constraints.” *Journal of Industrial Engineering and Management* 7 (1): 215–253.
Ravindran, A. R., R. U. Bilsel, V. Wadhwa, and T. Yang. 2012. “Risk Adjusted Multicriteria Supplier Selection Models with Applications.” *International Journal of Production Research* 48 (2): 405–424.
Ruiz-Torres, A. J., and F. Mahmoodi. 2007. “The Optimal Number of Suppliers Considering the Costs of Individual Supplier Failures. Omega: The.” *International Journal of Management Science* 35 (1): 104–115.
Sarykalin, S., G. Serraino, and S. Uryasev. 2008. “Value-at-risk vs. Conditional Value-at-risk in Risk Management and Optimization,” *Tutorials in Operations Research, INFORMS 2008*, 270–294.
Sawik, B. 2010a. “Selected Multi-Objective Methods for Multi-Period Portfolio Optimization by Mixed Integer Programming.” In *Applications of Management Science: Applications in Multi-Criteria Decision Making, Data Envelopment Analysis and Finance*. Vol. 14, edited by K. D. Lawrence and G. Kleinman, 3–34. Emerald: Bingley.
Sawik, B. 2012. “Downside Risk Approach for Multi-Objective Portfolio Optimization.” In *Operations Research Proceedings 2011*, edited by D. Klatte, H.-J. Lythi and K. Schmedders, 191–196. Springer: Berlin.
Sawik, T. 2010b. “Single vs. multiple objective supplier selection in a make to order environment. Omega: The.” *International Journal of Management Science* 38 (3–4): 203–212.
Sawik, T. 2011a. *Scheduling in Supply Chains Using Mixed Integer Programming*. NJ, Wiley: Hoboken.
Sawik, T. 2011b. “Selection of Supply Portfolio under Disruption Risks. Omega: The.” *International Journal of Management Science* 39: 194–208.
Sawik, T. 2011c. “Supplier Selection in Make-to-order Environment with Risks.” *Mathematical and Computer Modelling* 53 (9–10): 1670–1679.

Sawik, T. 2011d. "Selection of a Dynamic Supply Portfolio in Make-to-order Environment with Risks." *Computers and Operations Research* 38: 782–796.

Sawik, T. 2015. "Integrated Supply Chain Scheduling under Multi-level Disruptions." *IFAC-Papers On Line* 48 (3): 1515–1520.

Sawik, T. 2016a. "On the Risk-averse Optimization of Service Level in a Supply Chain under Disruption Risks." *International Journal of Production Research* 54 (1): 97–112.

Sawik, T. 2016b. "Integrated Supply, Production and Distribution Scheduling under Disruption Risks. Omega: The." *International Journal of Management Science* 62: 131–144.

Sawik, T. 2017. "A Portfolio Approach to Supply Chain Disruption Management." *International Journal of Production Research* 55 (7): 1970–1991.

Schmitt, A. J., and L. V. Snyder. 2012. "Infinite-horizon Models for Inventory Control under Yield Uncertainty and Disruptions." *Computers & Operations Research* 39: 850–862.

Scheibe, K. P., and J. Blackhurst. 2017. "Supply Chain Disruption Propagation: A Systemic Risk and Normal Accident Theory Perspective." *International Journal of Production Research*. doi:10.1080/00207543.2017.1355123.

Sen, A., H. Yaman, K. Guller, and E. Korpeoglu. 2014. "Multi-period Supplier Selection under Price Uncertainty." *Journal of the Operational Research Society* 65: 1636–1648.

Snyder, L. V., Z. Atan, P. Peng, Y. Rong, A. Schmitt, and B. Sinsoysal. 2016. "OR/MS Models for Supply Chain Disruptions: A Review." *IIE Transactions* 48 (2): 89109.

Stecke, K. E., and S. Kumar. 2009. "Sources of Supply Chain Disruptions, Factors that Breed Vulnerability, and Mitigating Strategies." *Journal of Marketing Channels* 16 (3): 193–226.

Tang, C. S. 2006. "Perspectives in Supply Chain Risk Management." *International Journal of Production Economics* 103: 451–488.

Tsai, W. C. 2016. "A Dynamic Sourcing Strategy Considering Supply Disruption Risks." *International Journal of Production Research* 54 (7): 2170–2184.

Ustun, O., and E. A. Demirtas. 2008. "An Integrated Multi-objective Decision Making Process for Multi-period lot Sizing with Supplier Selection. Omega: The." *International Journal of Management Science* 36: 509–521.

Wagner, S. M., K. J. Mizgier, and S. Papageorgiou. 2017. "Operational Disruptions and Business Cycles." *International Journal of Production Economics* 183: 66–78.

Ware, N. R., S. P. Singh, and D. K. Banwet. 2014. "A Mixed-integer Non-linear Program to Model Dynamic Supplier Selection Problem." *Expert Systems with Applications* 41: 671–678.

Wu, D., and D. L. Olson. 2008. "Supply Chain Risk, Simulation, and Vendor Selection." *International Journal of Production Economics* 114: 646–655.

Xanthopoulos, A., D. Vlachos, and E. Iakovou. 2012. "Optimal Newsvendor Policies for Dual-sourcing Supply Chains: A Disruption Risk Management Framework." *Computers & Operations Research* 39: 350–357.

Yu, H., A. Z. Zeng, and L. Zhao. 2009. "Single or Dual Sourcing: Decision-making in the Presence of Supply Chain Disruption rRisks. Omega: The." *International Journal of Management Science* 37: 788–800.

Yue, J., Y. Xia, and T. Tran. 2010. "Selecting Sourcing Partners for a Make-to-order Supply Chain. Omega: The." *International Journal of Management Science* 38: 136–144.