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On the fair optimization of cost and customer service level in a supply chain under disruption risks

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ABSTRACT

This paper presents a new decision-making problem of a fair optimization with respect to the two equally important conflicting objective functions: cost and customer service level, in the presence of supply chain disruption risks. Given a set of customer orders for products, the decision maker needs to select suppliers of parts required to complete the orders, allocate the demand for parts among the selected suppliers, and schedule the orders over the planning horizon, to equitably optimize expected cost and expected customer service level. The supplies of parts are subject to independent random local and regional disruptions. The fair decision-making aims at achieving the normalized expected cost and customer service level values as much close to each other as possible. The obtained combinatorial stochastic optimization problem is formulated as a stochastic mixed integer program with the ordered weighted averaging aggregation of the two conflicting objective functions. Numerical examples and computational results, in particular comparison with the weighted-sum aggregation of the two objective functions are presented and some managerial insights are reported. The findings indicate that for the minimum cost objective the cheapest supplier is usually selected, and for the maximum service level objective a subset of most reliable and most expensive suppliers is usually chosen, whereas the equitably efficient supply portfolio usually combines the most reliable and the cheapest suppliers. While the minimum cost objective function leads to the largest expected unfulfilled demand and the expected production schedule for the maximum service level follows the customer demand with the smallest expected unfulfilled demand, the equitably efficient solution ensures a reasonable value of expected unfulfilled demand.

1. Introduction

In global supply chain networks the optimization of material flows subject to unexpected disruption events, focuses on a variety of different optimality criteria. The most commonly used criteria for a global supply chain performance are minimization of cost and maximization of customer service level that measures the percentage of customer demand satisfied on time. The above two performance metrics are in conflict and, in addition, the decision makers often do not have preference to any objective, i.e., the two objectives are equally important. Then, an equitably efficient solution should be generated, in which the two normalized objective function values are as much close to each other as possible. Such kind of solutions can be generated by applying the lexicographic minimax method, as a special case of the ordered weighted averaging aggregation, e.g., Kostreva et al. [1], Ogryczak et al. [2]. The lexicographic minimax problem can be transferred to a lexicographic minimization problem and recently Liu and Papageorgiou [3] developed an approach to transfer the lexicographic minimax problem to a minimization optimization problem, instead of a lexicographic minimization problem, which needs to solve a sequence of optimization problems iteratively. The recent approach, however, is restricted to some special cases of a multiple objective problem (Liu et al. [4]).

The selection of part suppliers and allocation of order quantities under disruption risks may particularly help to optimize performance of a global supply chain network in the presence of unexpected disaster events (e.g., Park et al. [5], Fujimoto and Park [6], Schmitt and Singh [7]). Nevertheless, the research on supplier selection under disruption risks is limited, (e.g., Simangunsong et al. [8]). For example, Berger et al. [9], Berger and Zeng [10], Ruiz-Torres and Mahmoodi [11], Yu et al. [12] and Zeng and Xia [13] considered the impacts of supply disruption risks on the choice between single, dual and multiple sourcing strategies.

The literature on supply chain risk management indicates that the stochastic programming methodology has been successfully applied in a risk management related decision-making (e.g., [14,15]). In particular, stochastic mixed integer programming (stochastic MIP) is

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an appropriate tool for supply chain optimization under disruption risks due to its ability to handle uncertainty by probabilistic scenarios of disaster events as well as their outcomes. Stochastic programming allows for exact mathematical modeling approaches and optimization algorithms to be applied and the optimal solutions with respect to multiple relevant objective functions to be achieved. While the primary purpose of supply chain risk management is to avoid lower tail performances, stochastic MIP allows both the risk-neutral, average performance as well as the risk-averse, worst-case performance of a supply chain network to be optimized. For example, Li and Zabinsky [16] 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 et al. [17] proposed a scenario-based stochastic model for supplier selection in the presence of uncertain fluctuations of currency exchange rates and price discounts. Using a portfolio approach and the percentile measures of risk, Value-at-Risk (VaR) and Conditional Value-at-Risk (CVaR), Sawik [18–20] considered supplier selection and order quantity allocation in the presence of supply chain disruption risks. In particular in [19,20] a resilient supply portfolio was considered with fortified suppliers that are capable of supplying parts in the face of disruption events and with emergency [19] or regular [20] inventory pre-positioned at the fortified suppliers. The emergency inventory is used to compensate for the loss of capacity of the other suppliers, unprotected and hit by disruptions, while the regular inventory can be fully used under each disruption scenario to fulfill regular orders placed on the protected suppliers.

Most works on supply chains optimization focus on coordinating the flows of supply and demand over a supply chain network to minimize the inventory, transportation and shortage costs. However, the equitable optimization with respect to equally important conflicting objective functions (e.g., [3]) and under disruption risks is rarely considered as well as the associated coordinated scheduling of the disrupted material flows. Lei et al. [21] considered an integrated production, inventory and distribution routing problem involving heterogeneous transporters with non-instantaneous traveling times and many capacitated customer demand centers. A mixed integer programming (MIP) approach combined with a heuristic routing algorithm was proposed to coordinate the production, inventory and transportation operations. Bard and Nananukul [22] developed a MIP model and a reactive tabu search-based algorithm for a transportation scheduling problem that included a single production facility, a set of customers with time-varying demand and a fleet of vehicles. Wang and Lei [23] considered the problem of operations scheduling for a capacitated multi-echelon shipping network with delivery deadlines, where semi-finished goods are shipped from suppliers to customers through processing centers, with the objective of minimizing the shipping and penalty cost. The three polynomial-time solvable cases of this problem were reported: with identical order quantities; with designated suppliers; and with divisible customer order sizes. Sajadieh et al. [24] considered an integrated production-inventory model for a three-stage supply chain involving multiple suppliers, multiple manufacturers and multiple retailers, with stochastic lead times to retailers.

The major contribution of this paper is that it proposes a stochastic MIP model for the integrated selection of supply portfolio and scheduling of customer orders in a global supply chain under disruption risks to equitably optimize expected cost and expected customer service level. The supplies of parts are subject to independent random local and regional disruptions. The cost includes the cost of ordering, purchasing and shortage of parts, while the customer service level is a performance measure independent on any cost parameters, defined as the fraction of customer orders or customer demand, filled on or before their due dates. The equitable decision-making aims at achieving the normalized expected cost and customer service level values as much close to each other as possible. In order to obtain an equitably efficient solution to the combinatorial stochastic optimization problem, the ordered weighted averaging aggregation of the two conflicting objective functions is applied, e.g., Yager [25]. The stochastic MIP model proposed is based on the stochastic optimization approach presented in Sawik [26–28] for the integrated supplier selection, order quantity allocation and customer orders scheduling under disruption risks, where the problem objective was either to minimize expected cost or expected worst-case cost or to maximize expected service level or expected worst-case service level. In [26], the risk-neutral and the risk-averse solutions that minimize, respectively expected cost and expected worst-case cost were found for a single or multiple sourcing of different part types. The supplies were subject to independent random local disruptions of each supplier individually and to global disruptions of all suppliers simultaneously. The idea presented in [26] was further enhanced in [27] for the customer service level objective function and a single or dual sourcing strategy for a single critical part type. The suppliers were assumed to be located in two different geographic regions: in the producer's region (domestic suppliers) and outside the producer's region (foreign suppliers) and the supplies were subject to independent random local disruptions of each supplier individually and to regional disruptions of all suppliers in the same region simultaneously. Finally, the results achieved in [27] were enhanced in [28] for the risk-averse, single and multiple sourcing strategies under multi-regional disruption scenarios. Given a set of customer orders for products, the decision maker needs to decide which single supplier or which subset of suppliers to select for purchasing parts required to complete the customer orders and how to schedule the orders over the planning horizon, to mitigate the impact of disruption risks. The suppliers are located in different geographic regions and the supplies are subject to different types of disruptions: to random local disruptions of each supplier individually, to random regional disruptions of all suppliers in the same region simultaneously and to random global disruptions of all suppliers simultaneously. The problem objective was either to minimize the expected worst-case cost of ordering and purchasing of parts plus penalty cost of delayed and unfulfilled customer orders due to the parts shortages or to maximize the expected worst-case customer service level, i.e., the expected worst-case fraction of customer orders satisfied on time. In this paper, the two risk-neutral conflicting criteria: expected cost and expected customer service level are fairly optimized to achieve an equitably efficient supply portfolio and production schedule in the presence of supply chain disruption risks. The two alternative customer service level measures are compared: the expected fraction of satisfied on time customer orders or customer demand. The equitably efficient solutions obtained for the ordered weighted averaging aggregation of the two conflicting objective functions are compared with non-dominated solutions obtained using the weighted-sum aggregation approach.

The paper is organized as follows. The description of the integrated selection of supply portfolio and scheduling of customer orders with multiple suppliers subject to independent local and regional disruptions is presented in Section 2. The stochastic mixed integer programs for equitably efficient optimization of expected cost and expected customer service level are developed in Section 3. Numerical examples and some computational results, in particular comparison with the weighted-sum approach, are provided in Section 4, and final conclusions are made in the last section.

2. Problem description

In a supply chain under consideration various types of products are assembled over a planning horizon by a single producer to meet customer demand, using the same critical part type that can be manufactured and provided by different suppliers. Let $I=\{1,\dots,M\}$ be the set of M certified suppliers, $J=\{1,\dots,N\}$ the set of N customer orders for products, and $T=\{1,\dots,H\}$ the set of H planning periods.

Denote by a_j the unit requirement for the critical part of each product in customer order $j\in J$ and let b_j and d_j be, respectively the size and the due date of customer order $j\in J$. The total demand for all parts is $A=\sum_{j\in J}a_jb_j$ and the total demand for all products is $B=\sum_{j\in J}b_j$.

The orders for parts are assumed to be placed at the start of the planning horizon, when all customer orders for products are known. Let o_i be the unit purchasing price of parts from supplier $i\in I$ and denote by e_i the fixed cost of ordering parts from supplier $i\in I$. Each supplier have sufficient capacity to meet total demand for parts and to complete and prepare orders for shipping in a single planning period. Then, all parts ordered from a supplier are shipped together in a single delivery. The order preparation and transportation time of a shipment from supplier $i\in I$ to the producer is constant and equals to τ_i periods so that the parts ordered from supplier $i\in I$ are delivered in period τ_i and then can be used for the assembly of products in period τ_i+1, at the earliest.

Assume that the suppliers are located in a number of disjoint geographical regions and denote by $I^r\subseteq I$ the subset of suppliers in region $r\in R$, where $\bigcup_{r\in R}I^r=I$.

The supplies are subject to independent random local disruptions of each supplier individually and to random regional disruptions of all suppliers in the same geographical region simultaneously. Denote by p_i the local disruption probability for supplier $i\in I$ and by p^r the probability of regional disruption of all suppliers $i\in I^r$ in region $r\in R$. The regional disasters in each region and the local disasters at each supplier are assumed to be independent events. Let π_i be the disruption probability of every supplier $i\in I^r, r\in R$

$$\pi_i=p^r+(1-p^r)p_i;\quad i\in I^r, r\in R. \tag{1}$$

Denote by $S=\{1,\dots,q\}$ be the index set of all disruption scenarios, where each scenario $s\in S$ is composed of a unique subset $I_s\subset I$ of suppliers who deliver parts without disruptions. All potential disruption scenarios will be considered, that is $q=2^M$. For each scenario $s\in S$, the supplies from every supplier, $i\in I\setminus I_s$, can be disrupted either by a local or a regional disaster event. The probability P_s for disruption scenario $s\in S$ with the subset I_s of non-disrupted suppliers, and with all possible combinations of different disaster events considered, is [28]

$$P_s=\prod_{r\in R}P_s^r, \tag{2}$$

where P_s^r is the probability of realizing of disruption scenario s for suppliers in I^r

$$P_s^r=\begin{cases}(1-p^r)\prod\limits_{i\in I^r\bigcap I_s}(1-p_i)\prod\limits_{i\in I^r\setminus I_s}p_i & \text{if } I^r\bigcap I_s\neq\varnothing\\ p^r+(1-p^r)\prod\limits_{i\in I^r}p_i & \text{if } I^r\bigcap I_s=\varnothing.\end{cases} \tag{3}$$

The customer orders are single-period orders such that each order can be completed in one planning period. Assume that the producer has limited time-varying capacity, and denote by C_t the producer capacity available in planning period $t\in T$, and by c_j the unit capacity consumption for each product in customer order $j\in J$. The producer can be charged with a contractual, order specific penalty cost for delayed or unfulfilled customer orders, caused by the shortage of parts, that are delivered late or not at all due to supply disruptions. Let g_j and h_j be, respectively, the per unit and per period penalty cost of delayed customer order $j\in J$ and the per unit total penalty cost of unfulfilled customer order $j\in J$.

The objective of the equitable optimization of a supply chain under disruption risks is to allocate the total demand for parts among a subset of selected suppliers and to schedule the customer orders for products over the planning horizon to equitably minimize expected cost of ordering, purchasing and shortage of parts and maximize expected customer service level, i.e., the fraction of customer orders (or of customer demand) filled on or before their due dates. The resulting equitably efficient supply portfolio (the allocation of total demand for parts among the selected suppliers) is determined ahead of time as well as the equitably efficient schedule of customer orders for every potential disruption scenario.

3. Problem formulation

In this section the time-indexed stochastic MIP model **ECS** is proposed for the equitably efficient optimization of supplier selection and customer order scheduling to fairly minimize expected cost per product and maximize expected customer service level, i.e., the fraction of customer orders filled on or before their due dates. The following three basic decision variables are introduced in the proposed MIP model:

- Supplier selection variable: $u_i=1$, if supplier i is selected; otherwise $u_i=0$.
- Order-to-period assignment variable: $v_{jt}^s=1$, if under disruption scenario s customer order j is assigned to planning period t; otherwise $v_{jt}^s=0$.
- Demand allocation variable: $w_i\in[0,1]$ is the fraction of total demand for parts ordered from supplier i.

The demand allocation vector $(w_1,\dots,w_M)$, where $\sum_{i\in I}w_i=1$ and $0\le w_i\le 1, i\in I$, defines the selected supply portfolio, e.g., [18].

Let E_1 be the minimized expected cost per product and E_2, the maximized expected customer service level

$$E_1=\left(\sum_{i\in I}e_iu_i+\sum_{s\in S}P_s\left(\sum_{i\in I_s}Ao_iw_i+\sum_{j\in J}\sum_{t\in T:t>d_j}g_jb_j(t-d_j)v_{jt}^s+\sum_{j\in J}h_jb_j\left(1-\sum_{t\in T}v_{jt}^s\right)\right)\right)/B \tag{4}$$

$$E_2=\sum_{j\in J}\sum_{t\in T:t\le d_j}\sum_{s\in S}P_sv_{jt}^s/n. \tag{5}$$

In order to avoid dimensional inconsistency among various objectives, the values of the optimized objective functions are scaled into the interval [0,1]. Denote by $f_1=(E_1-\underline{E}_1)/(\overline{E}_1-\underline{E}_1)$, the normalized expected cost per product ($\underline{E}_1,\overline{E}_1$ are the minimum and the maximum values of E_1, respectively), and by $f_2=(\overline{E}_2-E_2)/(\overline{E}_2-\underline{E}_2)$, the normalized expected customer service level ($\underline{E}_2,\overline{E}_2$ are the minimum and the maximum values of E_2, respectively).

The normalized objective functions f_1 and f_2 are defined below:

$$f_1=\left(\left(\sum_{i\in I}e_iu_i+\sum_{s\in S}P_s\left(\sum_{i\in I_s}Ao_iw_i+\sum_{j\in J}\sum_{t\in T:t>d_j}g_jb_j(t-d_j)v_{jt}^s+\sum_{j\in J}h_jb_j\left(1-\sum_{t\in T}v_{jt}^s\right)\right)\right)/B-\underline{E}_1\right)/(\overline{E}_1-\underline{E}_1) \tag{6}$$

$$f_2 = \frac{\overline{E}_2 - \sum_{j \in J} \sum_{t \in T: t \le d_j} \sum_{s \in S} P_s v_{jt}^s / n}{(\overline{E}_2 - \underline{E}_2)}. \tag{7}$$

The mixed integer program **ECS** for the equitably efficient optimization of supplier selection and customer order scheduling to fairly minimize expected cost per products and maximize expected fraction of customer orders completed by their due dates is formulated below. The model is based on the stochastic MIP formulation proposed in [27]. The objective function (8) subject to constraints (9) represent the so-called ordered weighted averaging aggregation of the two conflicting criteria with equal weights assigned to each criterion (see, OWA aggregation, [25]). Applying OWA aggregation to the bi-criteria problem yields an equitably efficient solution to the problem, e.g., [3]. In the model presented below λ_l are unrestricted variables, while nonnegative variables δ_{kl} represent, for outcome values f_k, their upside deviations from the value of λ_l, e.g., Ogryczak and Tamir [29].

Model **ECS**: **E**quitably efficient supplier selection and customer order scheduling to minimize expected **C**ost and maximize expected **S**ervice level

Minimize

$$\sum_{l=1}^{2} \left(l\lambda_l + \sum_{k=1}^{2} \delta_{kl} \right) \tag{8}$$

subject to (6), (7) and

$$\lambda_l + \delta_{kl} \ge f_k; k, l = 1, 2 \tag{9}$$

Demand allocation constraints:

- the total demand for parts must be fully allocated among the selected suppliers,
- demand for parts cannot be assigned to non-selected suppliers,

$$\sum_{i \in I} w_i = 1 \tag{10}$$

$$w_i \le u_i; \ i \in I \tag{11}$$

Order-to-period assignment constraints:

- for each disruption scenario s, each customer order j is either scheduled during the planning horizon ($\sum_{t \in T} v_{jt}^s = 1$), or unscheduled and rejected ($\sum_{t \in T} v_{jt}^s = 0$),
- for each disruption scenario s and each planning period t, the cumulative demand for parts of all customer orders scheduled in periods 1 through t cannot exceed the cumulative deliveries of parts in periods 1 through $t-1$, from the non-disrupted suppliers $i \in I_s$,
- for each disruption scenario s, the total requirement for parts of scheduled customer orders is not greater than the total supplies from the non-disrupted suppliers $i \in I_s$,

$$\sum_{t \in T} v_{jt}^s \le 1; \ j \in J, s \in S \tag{12}$$

$$\sum_{j \in J} \sum_{t' \in T: t' \le t} a_j b_j v_{jt'}^s \le A \sum_{i \in I_s: \tau_i \le t-1} w_i; \ t \in T, s \in S \tag{13}$$

$$\sum_{j \in J} \sum_{t \in T} a_j b_j v_{jt}^s \le A \sum_{i \in I_s} w_i; \ s \in S \tag{14}$$

Producer capacity constraints:

- for any period t and each disruption scenario s, the total demand on capacity of all customer orders scheduled in period t must not exceed the producer capacity available in this period,

$$\sum_{j \in J} b_j c_j v_{jt}^s \le C_t; \ t \in T, s \in S \tag{15}$$

Non-negativity and integrality conditions:

$$\delta_{kl} \ge 0; k, l = 1, 2 \tag{16}$$

$$u_i \in \{0, 1\}; \ i \in I \tag{17}$$

$$v_{jt}^s \in \{0, 1\}; \ j \in J, t \in T, s \in S \tag{18}$$

$$w_i \in [0, 1]; \ i \in I. \tag{19}$$

In the above model, each supplier is assumed to have sufficient capacity to meet total demand for parts. Such an assumption allows the decision maker to select a single sourcing solution, if such a supply portfolio is an equitably efficient portfolio. However, the assumption can be easily relaxed to account for multiple capacitated suppliers, cf. Section 3.2.

3.1. Minimum and maximum values of the objective functions

In this subsection the minimum and maximum values for all objective functions are calculated to determine the normalized values of the objective functions, f_1, (6), f_2, (7), that is, the values of the optimized objective functions scaled into the interval [0,1]. Note that the cost and the service level objectives are in conflict. Therefore, the minimum and maximum values of expected cost $\underline{E}_1$, $\overline{E}_1$, and expected customer service level, $\underline{E}_2$, $\overline{E}_2$, are obtained by solving the following mixed integer programs:

Model **EC**: Supplier selection and customer order scheduling to minimize **E**xpected **C**ost per product

Minimize E_1, (4), subject to (10)–(15), (17)–(19).

Model **ES**: Supplier selection and customer order scheduling to maximize **E**xpected **S**ervice level

Maximize E_2, (5) subject to (10)–(15), (17)–(19).

In problem **EC**, E_1 is the minimized objective function, while E_2 is not considered. In problem **ES**, E_2 is the maximized objective function, while E_1 is not considered. Thus, by solving problem **EC**, the minimum value $\underline{E}_1$ of E_1 and the minimum value $\underline{E}_2$ of E_2 are determined. Similarly, by solving problem **ES**, the maximum value $\overline{E}_2$ of E_2 and the maximum value $\overline{E}_1$ of E_1 are determined.

So far, in the proposed models the customer service level is measured by the number of customer orders fulfilled by their due dates, with no account for the size of each customer order. For example, a high customer service level can be achieved by fulfilling a large number of small-size orders, while leaving the unfulfilled demand relatively high. To avoid such a solution, in particular when the customer orders of different size are simultaneously considered, the service level can be measured by the fraction of total customer demand fulfilled by the requested due dates.

If the customer service level is defined as the fraction of customer demand fulfilled by customer requested due dates, then E_2, (5) and f_2, (7) should be replaced with the following formulae, (20) and (21), respectively.

$$E_2 = \sum_{j \in J} \sum_{t \in T: t \le d_j} \sum_{s \in S} P_s b_j v_{jt}^s / B \tag{20}$$

$$f_2 = \frac{\overline{E}_2 - \sum_{j \in J} \sum_{t \in T: t \le d_j} \sum_{s \in S} P_s b_j v_{jt}^s / B}{(\overline{E}_2 - \underline{E}_2)}, \tag{21}$$

where $\underline{E}_2$, $\overline{E}_2$ are the minimum and the maximum values of E_2, (20), respectively. The values of $\underline{E}_2$, $\overline{E}_2$ can be determined using the models **EC** and **ES**.

In the computational examples presented in the next section, the two metrics of the customer service level will be considered and compared against each other.

3.2. Model limitations and possible enhancements

The proposed model has been developed to support decision-making in a make-to-order environment under disruption risks. The model, however, has been formulated under various simplified assumptions that may limit its practical usefulness. The basic assumptions are listed below.

1. A single critical part type is required to fulfill all customer orders for products.
2. The orders for parts are placed at the start of the planning horizon, when all customer orders for products are known.
3. Each supplier have sufficient capacity to meet the total demand for parts.
4. The order preparation time at each supplier is constant, independent of order size, and all parts ordered from a supplier are delivered during a fixed transportation time.
5. Transportation costs are not explicitly considered and the unit purchasing price from each supplier is constant, independent of total volume or value of order for parts, i.e., no quantity or business volume discounts are considered.
6. Transportation times to customers are not considered.
7. The local and regional disruptions are independent random events governed by Bernoulli distributions.
8. The customer orders are single-period orders such that each order must be completed in one planning period.
9. The penalty costs for delayed or unfulfilled customer demand are linear.
10. The inventory of parts and products are not considered.
11. The two conflicting objectives: reduction of expected cost and increase of expected customer service level are equally important for the decision maker.

Some of the above assumptions can be easily relaxed, while the other needs a more advanced model to be developed. Possible relaxations of the corresponding assumptions and the model enhancements are listed below.

1. The model can be easily enhanced for multiple part types required to fulfill all customer orders with different subsets of part types needed for different product types and different subsets of suppliers capable of providing different subsets of part types, e.g.,[26].
2. A rolling planning horizon approach can be used to account for a dynamic arrival and scheduling of customer orders as well as the corresponding supply portfolio. In practice, however, the supply portfolio needs to be decided at the start of the planning horizon, based on a forecast of the customer demand.
3. The model can be easily enhanced for multiple capacitated suppliers by the addition of suppliers capacity constraints.
4. The more advanced model can be developed to consider order-dependent processing and transportation times to better coordinate manufacturing and transportation of parts and production of finished products.
5. The model can be easily enhanced to account for quantity or business volume discounts (e.g., [30]) and the unit purchasing price from each supplier can include unit transportation cost.
6. Fixed transportation times to customers can be subtracted from customer requested delivery dates to determine the due dates for completing customer orders by the producer.
7. The dependencies among multiple unreliable suppliers and/or multiple unreliable geographic regions can be modelled by the correlated binomial distributions. Disruption risks can also be modelled as a Poisson jump process at a random magnitude, where the uncertain magnitude may reflect the severity of the disruption, ranging from total loss of supplier output to an uncertain portion of the output, e.g., Taylor and Karlin [31].
8. The model can be easily enhanced to account for large, multi-period customer orders that cannot be completed in one period and must be split into single-period portions to be processed in consecutive planning periods, e.g., Sawik [32].
9. The introduction of non-linear penalty costs may lead to a non-linear MIP model. The model, however, can be linearized in some cases, e.g., by using a piecewise linear representation of the non-linear penalty cost.
10. The model can be enhanced to account for the output inventory of parts at suppliers, the input inventory of parts at the producer and the output inventory of products waiting for shipment to customers. The inventory balance constraints can be added to the model and the producer inventory holding costs, to the cost-based objective function.
11. The number of conflicting and equally important objectives can be increased, for example by the addition of responsiveness (e.g., [3]) as another objective function.

4. Computational examples

In this section the proposed mixed integer programming approach for the equitably efficient supplier selection, order quantity allocation and customer orders scheduling in a supply chain under disruption risks is compared with the weighted-sum approach and illustrated with computational examples. The following parameters have been used for the example problems:

- $H=10$, $M=9$, $N=25$ and $q=2^M=512$;
- $R=\{1,2,3\}$, and $I^1=\{1,2,3\}$, $I^2=\{4,5,6\}$, $I^3=\{7,8,9\}$;
- τ_i, the order preparation and shipping times from suppliers were 2, 3 and 4 time periods, respectively for suppliers $i \in I^1$, $i \in I^2$ and $i \in I^3$;
- $a_j \in \{1,2,3\}$, $b_j \in \{500, 1000, \dots, 5000\}$, $c_j \in \{1,2,3\}$, $d_j \in \{1+\min_{i \in I}(\tau_i), \dots, H\}$;
- C_t, the capacity of producer in each period t, was integer drawn from $1000\lceil(2\sum_{j \in J} b_j c_j/(H-\max_{i \in I}\tau_i))U[0.75;1.25]/1000\rceil$ distribution, i.e., in each period the producer capacity was from 75% to 125% of the double capacity required to complete all customer orders during the planning horizon, after the latest delivery of parts;
- $e_i \in \{5000, 6000, \dots, 10{,}000\}$, $i \in I^1$, $e_i \in \{10{,}000, 11{,}000, \dots, 15{,}000\}$, $i \in I^2$ and $e_i \in \{15{,}000, 11{,}000, \dots, 30{,}000\}$, $i \in I^3$;
- o_i, the unit price of parts purchased from supplier i, was uniformly distributed over [11,16], [6,11] and [1,6], respectively for suppliers $i \in I^1$, $i \in I^2$ and $i \in I^3$;
- $g_j = \lceil a_j \max_{i \in I}(o_i)/350\rceil$, $j \in J$, i.e., the unit penalty cost per period for each delayed customer order j was approximately 0.28% of the maximum unit price of required parts;
- $h_j = 2\lceil a_j \max_{i \in I}(o_i)\rceil$, $j \in J$, i.e., the unit penalty cost for each unfulfilled customer order j was approximately twice as large as the maximum unit price of required parts;
- p_i, the local disruption probability was uniformly distributed over [0.005,0.01], [0.01,0.05] and [0.05;0.10], respectively for suppliers $i \in I^1$, $i \in I^2$ and $i \in I^3$;
- $p^1=0.001$, $p^2=0.005$ and $p^3=0.01$.

The detailed data set was based on the example presented in [26], e.g.,: unit requirements for parts, $a=(2,1,3,3,1,3,2,1,2,2,2,3,2,1,3,2,1,3,3,2,1,1,2,1)$; size of customer orders, $b=(1,2,9,7,8,5,1,7,5,4,7,4,10,6,8,1,4,2,4,8,6,3,8,7,3)\times 500$, (the resulting total demand for parts and products is $A=132{,}500$ and $B=66{,}000$, respectively); unit capacity consumption, $c=(2,1,1,2,3,3,1,3,2,1,2,1,3,1,1,3,2,3,1,1,3,2,2,1,2)$; producer available capacity, $C_t=C=38{,}000$, $\forall t=1,\dots,10$; unit prices, $o=(13,12,12,8,6,6,2,5,4)$; local disruption probabilities, $p=(0.00513571, 0.00666354, 0.00902974, 0.0356206, 0.040175, 0.0294692, 0.0519967, 0.0827215, 0.0739062)$; and the corresponding disruption probabilities (1), $\pi=(0.00613057, 0.00765688, 0.0100207, 0.0404425, 0.0449741, 0.0343219, 0.0614767, 0.0918943, 0.0831672)$.

Note that the constant producer capacity, $C = 38{,}000$, allows for completing all customer orders in at most $\lceil \sum_{j\in J} b_j c_j / C \rceil = \lceil 3.26 \rceil = 4$ planning periods, that is, in less than $(H - \max_{i\in I}\tau_i) = 6$ periods remaining in the planning horizon after the latest delivery of parts.

In the computational experiments all potential disruption scenarios, $q = 2^M = 512$, and all possible combinations of local and regional disaster events were considered. Each scenario $s\in S$ with the subset I_s of non-disrupted suppliers is represented by an M-dimensional 0 -1 vector with 1, if $i\in I_s$, i.e., if supplier i is not disrupted, and 0; otherwise. The corresponding disruption probability, P_s, for each scenario $s\in S$ was calculated using formulae (2) and (3).

The unit price per part o_i and the disruption probability π_i, (1), of each supplier $i\in I$ are shown in Fig. 1. The figure indicates that the most reliable (with the lowest disruption probability, $\pi_1 = 0.00613057$) is supplier 1, the least reliable (with the highest disruption probability, $\pi_8 = 0.0918943$) is supplier 8, the most expensive (with the highest price per part, $o_1 = 13$) is supplier 1, and the cheapest (with the lowest price per part, $o_7 = 2$) is supplier 7. Note that the geographic regions are numbered in such a way that the unit prices are nonincreasing with r, while the fixed ordering costs and the disruption probabilities are nondecreasing with r, i.e.,

$$o_{i_1} \ge o_{i_2} \ge o_{i_3}, \quad e_{i_1} \le e_{i_2} \le e_{i_3} \quad \text{and}$$
$$\pi_{i_1} \le \pi_{i_2} \le \pi_{i_3};\ \forall\, i_1 \in I^1, i_2 \in I^2, i_3 \in I^3.$$

The solution results are presented in Table 1. In addition to the optimal absolute and normalized solution values for the primary objective functions and the allocation of demand among the selected suppliers, Table 1 presents the expected values of the associated objective function, i.e., the minimum expected customer service level, $\underline{E}_2$, for model **EC** and the maximum expected cost per product, $\overline{E}_1$, for model **ES**. Table 1 indicates that for the cost-based objective (model **EC**) the cheapest supplier $i=7$ is selected only, while for the customer service level (model **ES**), the total demand for parts is allocated among the three most reliable and most expensive suppliers $i = 1,2,3$ for objective (5), and among the two suppliers $i=1,2$ for objective (20). For the equitable solution (model **ECS**), the supply portfolio contains one reliable and expensive supplier $i=2$ and two low-cost and unreliable suppliers $i=6,7$ for both (7) and (21), service level objectives.

As an illustrative example, Fig. 2 presents the demand for products, $\sum_{j\in J: d_j = t} b_j, t\in T$, and the expected production schedules, $\sum_{s\in S} P_s \sum_{j\in J} b_j v^s_{jt}, t\in T$ for the optimal cost, optimal customer service level and for the equitably efficient solution. Fig. 2 compares the expected production schedules for the two different metrics of customer service level: (a) the percentage of customer orders fulfilled on time, (5), and (b) the percentage of customer demand fulfilled on time, (20). While for the two different service level metrics, the corresponding supply portfolios are very similar (cf. Table 1), and the expected production schedules with respect to the two service level objectives are also very similar, the corresponding schedules for the equitably efficient solutions are different.

In general, the service level-based solution, when no cost components are included in the objective function, better meets the customer demand, with the smallest fraction of unfulfilled demand. The total customer demand is met with only a small fraction of the expected unfulfilled demand: 0.0615 for the cost-based solution, 0.0055 for the service level-based solution (a), 0.0051 for the service level-based solution (b), 0.0468 for the

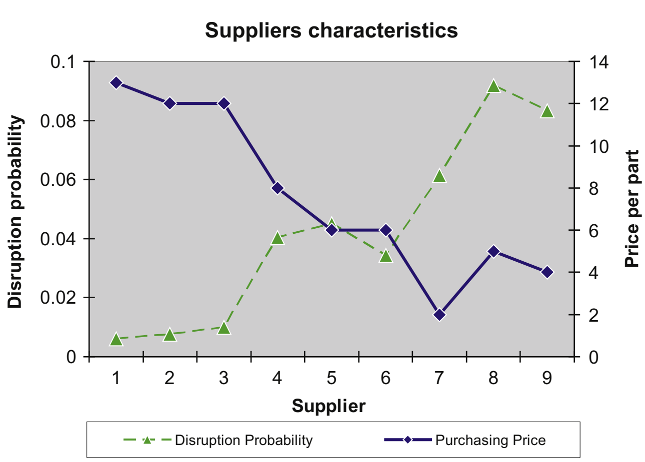

Fig. 1. Basic characteristics of suppliers.

Table 1
Solution results.

Model **EC**: Var. = 100468, Bin. = 100459, Cons. = 21341, Nonz. = 765902[a]	
Expected cost ($\underline{E}_1$)	7.66
Suppliers selected (% of total demand)	7(100%)
Expected service level ($\underline{E}_2$)	67.60%[b],66.32%[c]
Model **ES**: Var. = 100468, Bin. = 100459, Cons. = 21341, Nonz. = 765902[a]	
Expected service level ($\overline{E}_2$)	99.62%[b]
Suppliers selected (% of total demand)	1(48%),2(31%),3(21%)
Expected cost ($\overline{E}_1$)	25.64
Model **ECS**: Var. = 100476, Bin. = 100459, Cons. = 21347, Nonz. = 921880[a]	
Expected cost	9.31
Expected service level	96.06%[b]
Normalized expected cost	0.098
Normalized expected service level	0.111
Suppliers selected (% of total demand)	2(6%),6(13%),7(81%)
Model **ES** with (5) replaced by (20)	
Expected service level ($\overline{E}_2$)	99.49%[c]
Suppliers selected (% of total demand)	1(55%), 2(45%)
Expected cost ($\overline{E}_1$)	25.61
Model **ECS** with (7) replaced by (21)	
Expected cost	9.25
Expected service level	95.29%[c]
Normalized expected cost	0.088
Normalized expected service level	0.127
Suppliers selected (% of total demand)	2(6%), 6(10%), 7(84%)

[a] Var. = number of variables, Bin. = number of binary variables. Cons. = number of constraints, Nonz. = number of nonzero coefficients.
[b] $(\sum_{s\in S} P_s \sum_{j\in J} \sum_{t\in T: t\le d_j} v^s_{jt}/n)100\%$.
[c] $(\sum_{s\in S} P_s \sum_{j\in J} \sum_{t\in T: t\le d_j} b_j v^s_{jt}/B)100\%$.

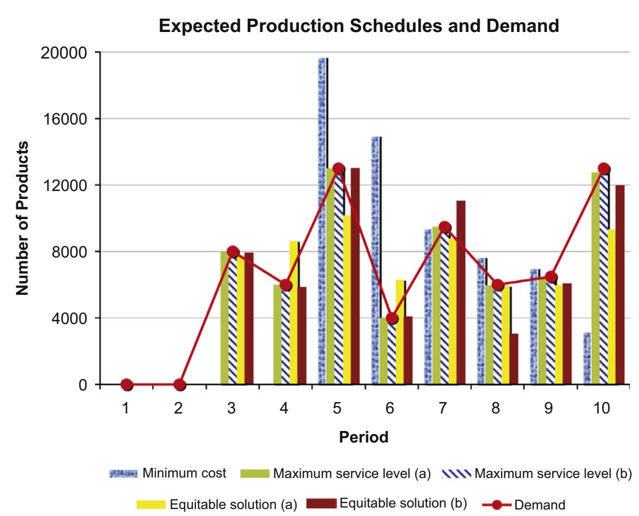

Fig. 2. Expected production schedules, customer service level in: (a) % of customer orders fulfilled on time; and (b) % of customer demand fulfilled on time.

equitably efficient solution (a), and 0.0470 for the equitably efficient solution (b). In addition, for the service level-based objective functions, the expected production schedule approximately follows the customer demand pattern, while for the minimum cost objective function the most unbalanced production schedule is achieved. Since all parts are delivered by the cheapest supplier 7 in period 4, the production begins only in period 5.

In order to compare the solution results for the two different service level-based objective functions (5) and (20), the computational experiments were repeated for another example with more diversified size of customer orders, $b_j \in \{500, 1000, \ldots, 12,000\}$, i.e., from 500 to 12,000 products, for the same total demand for parts and products, $A = 132,500$ and $B = 66,000$. The solution results are presented in Table 2, and Fig. 3 compares the expected production schedules for the two different metrics of customer service level. In general, the results presented in Table 2 are similar to those in Table 1, in particular the supply portfolios are very similar. However, Fig. 3 shows that for the more diversified customer orders, the less smoothed expected production schedules are obtained for the equitably efficient solutions. On the other hand, Table 2 shows that the equitably efficient solutions with a perfect equity were found (i.e., with identical values of normalized expected cost and normalized expected customer service level), which indicates that the obtained supply portfolios and schedules of customer orders are also the lexicographic minimax optimal solutions as well as the Pareto-optimal solutions (see, [3,4]).

The solution results demonstrate that for the minimum cost objective the cheapest supplier is usually selected, for the maximum service level objective a subset of most reliable and most expensive suppliers is usually chosen, whereas the equitably efficient supply portfolio usually combines the two types of suppliers.

4.1. Weighted-sum approach

The equitably efficient solutions obtained using model **ECS** have been compared with the non-dominated solutions obtained by minimizing the weighted-sum aggregation of the two normalized objective functions, f_1, (6) and f_2, (21), i.e., the weighted-sum of expected cost per product and expected fraction of customer demand fulfilled by requested due dates. The weighted-sum model **WCS** is shown below and the solution results for the example with similar and diversified customer orders are presented in Tables 3 and 4, respectively.

Model **WCS**: Supplier selection and customer order scheduling to minimize **W**eighted-sum of normalized expected **C**ost and normalized expected **S**ervice level

Minimize

$$\lambda f_1 + (1-\lambda) f_2, \tag{22}$$

where $0 \le \lambda \le 1$, subject to (6), (10)–(15), (17)–(19), (21).

Tables 3 and 4 indicate that for $\lambda = 1$ (minimization of cost) the cheapest supplier $i = 7$ is selected only, while for $\lambda = 0$ (maximization of customer service level) the total demand for parts is allocated among the two most reliable and most expensive suppliers $i = 1,2$. As λ increases from 0 to 1, i.e., the decision maker preference shifts from customer service level to cost, more demand is moved from expensive and reliable suppliers to low-cost, unreliable suppliers. For the example with similar customer orders, the subset of non-dominated solutions contains (for $\lambda = 0.3$, 0.4) the optimal solution obtained for model **ECS** with constraint (21) (cf., Tables 1 and 3). In contrast to the example with diversified customer orders (cf., Tables 2 and 4). For diversified orders, Fig. 4 shows the non-dominated supply portfolios (the allocation of total demand for parts among selected suppliers) for 11 levels of trade-off parameter λ. The subset of selected suppliers consists of four suppliers $i = 1, 2, 6, 7$ of which suppliers $i = 1,2$ are most reliable and suppliers $i = 6,7$ are the cheapest suppliers in region $r = 2,3$, respectively.

For the example with diversified customer orders, the trade-off between the expected cost and the expected customer service level is clearly shown in Fig. 5, where the efficient frontier is presented. The results emphasize the effect of varying service level/cost preference of the decision maker; the higher the trade-off parameter λ, the more cost-oriented the decision making.

The computational experiments were performed using the AMPL programming language and the CPLEX 12.5 solver on a MacBookPro laptop with Intel Core i7 processor running at 2.8 GHz and with 16 GB RAM. The solver was capable of finding proven optimal solution for all examples with CPU time ranging from several seconds to several hours.

Table 2
Solution results: diversified customer orders.

Model **EC**	
Expected cost ($\underline{E}_1$)	7.44
Suppliers selected (% of total demand)	7(100%)
Expected service level ($\underline{E}_2$)	71.32%[a], 78.83%[b]
Model **ES**	
Expected service level ($\overline{E}_2$)	99.77%[a]
Suppliers selected (% of total demand)	1(42%), 2(41%), 3(17%)
Expected cost ($\overline{E}_1$)	25.15
Model **ECS**	
Expected cost	9.38
Expected service level	97.48%[a]
Normalized expected cost	0.110
Normalized expected service level	0.110
Suppliers selected (% of total demand)	2(3%), 6(22%), 7(75%)
Model **ES** with (5) replaced by (20)	
Expected service level ($\overline{E}_2$)	99.47%[b]
Suppliers selected (% of total demand)	1(65%), 2(35%)
Expected cost ($\overline{E}_1$)	25.43
Model **ECS** with (7) replaced by (21)	
Expected cost	10.44
Expected service level	95.99%[b]
Normalized expected cost	0.168
Normalized expected service level	0.168
Suppliers selected (% of total demand)	2(3%), 5(5%), 6(30%), 7(62%)

[a] $(\sum_{s \in S} P_s \sum_{j \in J} \sum_{t \in T: t \le d_j} v^s_{jt}/n)100\%$.
[b] $(\sum_{s \in S} P_s \sum_{j \in J} \sum_{t \in T: t \le d_j} b_j v^s_{jt}/B)100\%$.

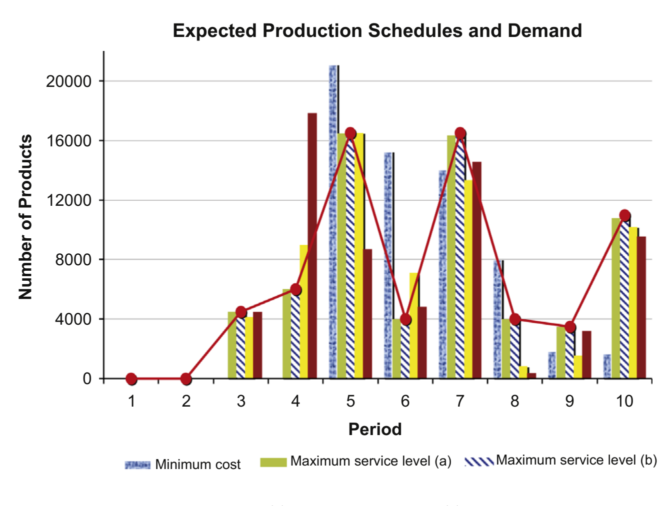

Fig. 3. Expected production schedules for diversified customer orders, customer service level in: (a) % of customer orders fulfilled on time; and (b) % of customer demand fulfilled on time.

Table 3
Non-dominated solutions.

λ	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
	Var. = 100470, Bin. = 100459, Cons. = 21343, Nonz. = 921868[a]										
Expected cost	25.61	19.40	11.93	9.25	9.25	8.88	8.88	8.88	8.88	8.01	7.66
Expected service level[b]	99.48	98.57	96.86	95.29	95.29	94.73	94.73	94.73	94.73	82.69	66.32
Normalized expected cost	1	0.654	0.238	0.088	0.088	0.068	0.068	0.068	0.068	0.020	0
Normalized expected service level	0	0.028	0.079	0.127	0.127	0.143	0.143	0.143	0.143	0.506	1
Suppliers selected	1(55)	1(6)									
(% of total demand)	2(45)	2(44)	2(10)	2(6)	2(6)	2(6)	2(6)	2(6)	2(6)		
		6(50)	6(40)	6(10)	6(10)	6(5)	6(5)	6(5)	6(5)	6(5)	
			7(50)	7(84)	7(84)	7(89)	7(89)	7(89)	7(89)	7(95)	7(100)

[a] Var. = number of variables, Bin. = number of binary variables, Cons. = number of constraints, Nonz. = number of nonzero coefficients.
[b] $(\sum_{s\in S}P_s\sum_{j\in J}\sum_{t\in T:t\le d_j}b_j v^s_{jt}/B)100\%$.

Table 4
Non-dominated solutions: diversified customer orders.

λ	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
	Var. = 100470, Bin. = 100459, Cons. = 21343, Nonz. = 921868[a]										
Expected cost	25.43	24.81	12.95	11.00	8.61	8.61	8.31	8.31	8.31	8.31	7.44
Expected service level[b]	99.47	99.42	97.07	96.30	94.90	94.90	94.45	94.45	94.45	94.45	78.83
Normalized expected cost	1	0.9655	0.3062	0.1977	0.0650	0.0650	0.0486	0.0486	0.0486	0.0486	0
Normalized expected service level	0	0.0025	0.1169	0.1532	0.2226	0.2224	0.2439	0.2440	0.2442	0.2446	1
Suppliers selected	1(65)	1(33)									
(% of total demand)	2(35)	2(67)	2(13)	2(8)	2(4)	2(4)	2(3)	2(3)	2(3)	2(3)	
			6(53)	6(35)	6(9)	6(9)	6(5)	6(5)	6(5)	6(5)	
			7(34)	7(57)	7(87)	7(87)	7(92)	7(92)	7(92)	7(92)	7(100)

[a] Var. = number of variables, Bin. = number of binary variables, Cons. = number of constraints, Nonz. = number of nonzero coefficients.
[b] $(\sum_{s\in S}P_s\sum_{j\in J}\sum_{t\in T:t\le d_j}b_j v^s_{jt}/B)100\%$.

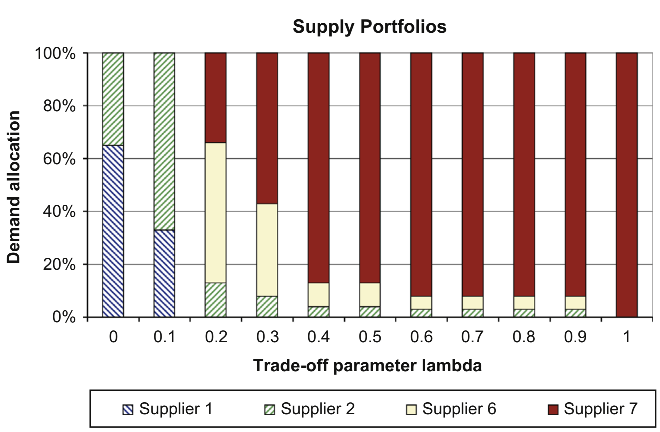

Fig. 4. Non-dominated supply portfolios: diversified customer orders.

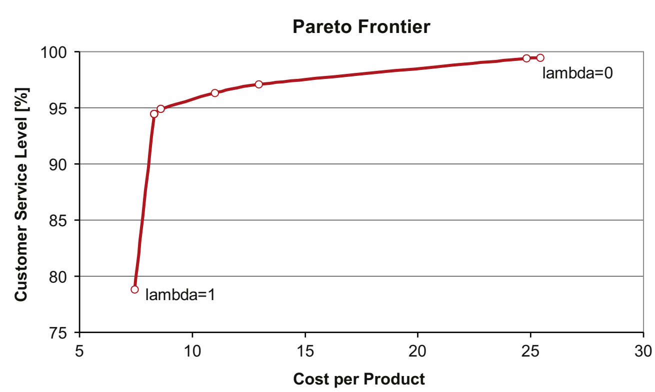

Fig. 5. Customer service level vs. Cost per product: diversified customer orders.

5. Conclusions

This paper considers the equitably efficient decision-making problem associated with supplies of parts and deliveries of finished products in the presence of supply chain disruption risks. The supplies are subject to independent random local disruptions associated with a particular supplier and to random regional disruptions that may result in disruption of all suppliers in the same geographic region simultaneously. The obtained combinatorial stochastic optimization problem of equitably efficient minimization of expected cost and maximization of expected customer service level has been formulated as a stochastic mixed integer program with the ordered weighted averaging aggregation of the two objective functions. The decision maker objective is to fairly optimize an average performance of the supply chain with respect to the two equally important and conflicting optimality criteria. The equitably efficient solution (the supply portfolio and the schedule of customer orders) aims at achieving the normalized expected cost and customer service level values as much close to each other as possible. While for the minimum cost objective the cheapest supplier is usually selected, and for the maximum service level objective a subset of most reliable and most expensive suppliers is usually chosen, the equitably efficient supply portfolio usually combines the two types of suppliers: the cheapest suppliers from among the most reliable and the most reliable from among the cheapest. Comparison of expected production schedules for the minimum cost and the maximum service level objective functions indicates that for the latter objective the expected production follows the customer demand with the minimum expected fraction of unfulfilled demand. While the expected fraction of unfulfilled customer demand is largest for the minimum cost objective function, the equitably efficient solution leads to medium values of the expected unfulfilled demand.

The computational experiments have indicated that the equitably efficient solutions with a perfect equity can sometimes be found, which indicates that the obtained solutions can also be the lexicographic minimax optimal solutions as well as the Pareto-optimal solutions (see, [3,4]). Comparison with the weighted-sum approach which generates a subset of non-dominated solutions indicates that the lexicographic minimax optimal solution may not be found using that approach.

In the proposed model, each supplier is assumed to have sufficient capacity to meet total demand for parts, which allows the decision maker to select a single sourcing type of a supply portfolio, if it is an equitably efficient solution. In the future research, however, that assumption can be easily relaxed to account for multiple capacitated suppliers. Furthermore, the other assumptions can also be relaxed to develop a more advanced model (for possible model relaxations and enhancements, see Section 3.2). In particular, the future research should focus on a robust decision-making in a supply chain under disruption risks to obtain an equitably efficient performance of a supply chain in average-case as well as in the worst-case, which reflects the decision makers requirements to maintain an equally good performance of a supply chain under different conditions. The robust decision making would aim at equitably efficient solution that fairly optimizes the expected value and the expected worst-case value, i.e., Conditional Value-at-Risk of the selected objective function.

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