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RISK AVERSE DECISION MODELS FOR RESILIENT SUPPLIER SELECTION

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Abstract: Decision models provided by this study aim to help managers to find remedies to devastating supply chain disruptions that could be caused by a mismatch between volatile customer demand and unreliable supply. We considered the newsvendor problem where the firm has more than one suppliers who are not necessarily reliable. We have provided a range of decision models with risk neutral and risk averse objective functions. The model uses scenarios to represent uncertain events (specifying customer demand and supplier reliability). Linear Programming formulations are provided which can be easily solved using commercially available software. A sample numerical study is also carried out to provide valuable managerial insights for optimal sourcing behaviors of risk averse and risk neutral firms. In the numerical study, expected profit, CVaR and Mean Excess Regret models are selected for evaluation.

Keywords: *Newsvendor problem, supply chain disruptions, supplier selection, risk management.*

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TEDARİKÇİ SEÇİMİ İÇİN RİSK GÖZETEN KARAR MODELLERİ

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Öz: Bu çalışmanın amacı arz talep dengesizliğinden dolayı tedarik zincirinde oluşacabilecek kesintilerin yıkıcı etkilerini azaltmak için karar modelleri sunmaktır. Bu çalışmada birden çok güvenilir olmayan tedarikçisi olan "Gazeteci" problemi ele alınmıştır. Risk gözeten ve risk karşıtı farklı modeller sunulmuştur. Gelecekteki tüketici talebi ve tedarikçi güvenilirliği senaryolarla belirlenmiştir. Problemler optimizasyon amaçlı yazılımlarla kolayca çözülebilen "Doğrusal Programlama" yöntemi ile modellenmiştir. Yöneticilere tedarikçi seçimlerinde yol gösterici stratejiler üretmek amacı ile örnek bir sayısal çalışma da yapılmıştır. Bu sayısal çalışmada ortalama kar, CVaR ve ortalama artık pişmanlık yöntemleri uygulanmıştır.

Anahtar Sözcükler: *Gazeteci problemi, tedarik zinciri kesintileri, tedarikçi seçimi, risk yönetimi.*

INTRODUCTION

This is an age of continuous technological advances, decreasing product life cycles, volatile and unpredictable markets. The manufacturer has to make sourcing, production and inventory decisions based on anticipated demand in future periods. In this business environment, companies can only stay competitive if they can respond customer needs fast and efficiently. Firms have been adopting Just-In-Time and Lean strategies to increase their efficiency. Such strategies recommend firms to decrease inventory levels, subcontract noncore activities, and sustain long-term relationships with reduced number of suppliers. There are several reasons why Just-In-Time and Lean strategies advocate reduced number of suppliers. Some reasons for single sourcing include the high costs of product design, supplier learning curve effects, increased bargaining power of the firm to negotiate on price, lead times, payment, quality and delivery flexibility (Minner, 2003).

Recently firms have become part of supply chains which involve a complex network of global suppliers and partners. Globalization has offered companies wonderful opportunities to concurrently decrease cost and strategically enhance the competitive position of the company. On the other hand, while improving competitiveness of a company; global sourcing might also cause significant risk in supply chains increasing prices due to natural disasters, volatility of oil prices, exchange rate fluctuations, terrorist attacks, geopolitical uncertainty, port/custom delays etc.

Several firms found themselves unprepared for the elevated supply chain risk while they were focusing on improving efficiency through "*lean*" solutions. Ignoring or underestimating the risk in global supply chains, or not having suitable mitigation strategies would cause devastating outcomes. The following examples are excellent examples for the need of higher degree of resilience due to higher level of supply chain risk. After the earthquake and tsunami in Japan in 2011, supply chains with a single source which is located in the region confronted the overwhelming outcomes of the disruption (Chopra, Meindl, 2013). In another case, the fire occurred in 2001 in a Philips Electronics plant in New Mexico interrupted the supply of critical cellphone components to: Ericsson and Nokia. As opposed to Ericsson, Nokia found an alternate supply source in three days. Due to component shortages, Ericsson reported long-term losses of $2.34 billion and ultimately withdrew from the cell phone market (Christopher, Peck, 2004). Another well-known supply disruption example is about Aisin who provided 90% of all brake parts components for Toyota before it was destroyed by a fire in 1997 (Nishiguchi, Beaudet, 1998). Toyota's assembly plants were forced to shut down after a fire at Aisin's main plant. Toyota's net income from this event decreased around $300 million. After this event, Toyota has decided to maintain at least two suppliers for each part (Treece, 1997).

The examples above clearly indicated that it is critical for supply chains to adopt suitable mitigation strategies which should also define sourcing preferences of the firms. Sourcing from a low-cost supplier, eliminating excess capacity and redundant suppliers may make supply chains more cost efficient in the short term while making them vulnerable to disruptions in the long run (Chopra, Sodhi, 2014). Disruption risk can be mitigated by adopting multiple sourcing strategies. After selecting a set of suppliers, the firm must then determine the best allocation of product requirements among them considering various factors such as supplier's price, yields, lead times, and transportation costs.

This paper focuses on supplier related decisions as a mechanism for matching supply with demand. Specifically, supplier-related decisions in a classical newsvendor setting are considered. The traditional newsvendor model assumes that a single supplier exists and there is no uncertainty. This paper's focus is to explore the additional challenges associated with having multiple unreliable suppliers. The traditional newsvendor model objective is based on risk neutrality maximizing expected long term returns while this study explores the effects of risk aversion on supplier selection decisions. Risk aversion can be described as a decision maker's hesitancy to accept a choice with an uncertain payoff rather than another choice with more certain but possibly lower expected payoff. When supply risks are present and customer demand is volatile, considering risk aversion in procurement selection models makes sense as maximizing expected profit would result several consecutive large losses which could be devastating for a firm.

1. LITERATURE REVIEW

Khouja (1999) and Qin *et al*. (2011) provides a survey of research on newsvendor problems. Elmaghraby (2000) and Minner (2003) offer a e review of the literature on multiple supplier inventory models in supply chain management.

Gallego and Moon (1993) first presented the supplier yield into the newsvendor literature. Anupindi and Akella (1993) studied both single and multi-period models with uncertain stochastic demand and supplier reliability concluding that it is always optimal to order some amount from the low cost supplier. Agrawal and Nahmias (1997) studied a supplier selection problem with multiple unreliable suppliers. They assumed a deterministic demand and normally distributed supplier reliabilities. In addition, they assumed that a fixed order cost is incurred for each supplier with a positive order. Dada *et al*. (2007) studied the differences in sourcing strategies when suppliers are completely reliable and when they are unreliable. They concluded that even perfect reliability is no guarantee for qualification of a supplier since, in an optimal solution, a given supplier will be selected only if all less-expensive suppliers are selected. Burke *et al*. (2007)

examined the influence of supplier pricing arrangements and supplier capacity restrictions on the optimal sourcing strategies for a single firm. Burke *et al.* (2009) explored the consequences of uncertain supplier reliability on a firm's sourcing decisions with stochastic demand. They described specific conditions under which a firm should choose a single supplier strategy versus multiple supplier sourcing strategy. Merzifonluoglu and Feng (2014) developed an exact solution algorithm to find the optimal solution for the supplier selection problem where customer demand and supplier reliabilities follow normal distribution.

We also reviewed research focusing on risk averse decision models for the newsvendor setting. Lau (1980) considered two objectives, maximizing expected utility and maximizing the probability of achieving a budgeted profit. Eeckhoudt *et al.* (1995) studied the risk aversion with the use of an expected utility criterion concluding that a risk-averse newsvendor will order strictly less than a risk-neutral newsvendor. Wang and Webster (2009) studied the loss-averse newsvendor problem while Wu *et al.* (2009) studied a mean–variance objective. Gotoh and Takano (2007) studied the newsvendor problem with a CVaR objective. They provided analytical solutions under mild assumptions. Jammernegg and Kischka (2012) provided a comparative analysis of VaR and CVaR in the newsvendor problem.

This paper will contribute to the state of knowledge by combining unreliable supplier selection decisions of a newsvendor with variety of risk measures. Sawik (2011) is the closest study to ours while their model is limited to known customer demands. In this study we assume that customer demand is uncertain. They studied the supplier selection problem in a make-to-order environment and only applied the VaR and CVaR measures while this study considers a variety risk measures. To our knowledge, this is the first study who applies "α-Reliable Mean Excess Regret" method to a unreliable supplier selection problem. This study fills the research gap presenting various optimization models for the optimal selection of supply portfolio under a variety of risk measures. These risk measures have all appeared in the literature on various stochastic optimization models but have not previously been used for supplier disruption problems. The focus is on the formulation of and analysis of these models and the derivation of managerial insights from the solutions.

2. MATHEMATICAL MODELS

We consider an extension of the newsvendor problem where the firm orders from several suppliers which are subject to complete disruptions. If the total supply is less than the realized demand, there will be lost demand; and if the total supply exceeds the realized demand, then the firm will have leftovers to be salvaged.

The notation that will be used throughout this paper is given below.
i Index for a supplier.
N Number of suppliers.

Problem Parameters:
r Revenue per unit due to consumption.
w Salvage value.
o Lost sale penalty.
c_i Unit ordering cost of supplier i (we assume that supplier only pays for the units it receives).

Random Variables:
R_i Random variable denoting the reliability of a supplier i.
D Random demand to be satisfied by the firm.

Scenarios:
U Number of possible scenarios.
P_u Probability of occurrence of scenario u.
R_{iu} Realized reliability of supplier i in scenario u.
D_u Realized customer demand in scenario u.

Decision Variables:
q_i Decision variable for the amount ordered from the supplier i.
ζ_u Excess demand in scenario u that is not satisfied by suppliers.
$\zeta_u =$ $(D_u - \sum_{i \in N} q_i R_{iu})^+$
ψ_u Profit of scenario u.
$\psi_u =$ $rD_u - \sum_{i \in N} c_i q_i R_{iu} - (r+o)(D_u - \sum_{i \in N} q_i R_{iu})^+ + w(\sum_{i \in N} q_i R_{iu} - D_u)^+$
$\psi_u =$ $(r-w)D_u - \sum_{i \in N}(c_i - w) q_i R_{iu} - (r+o-w)\zeta_u$

The objective is to choose the optimal supplier portfolio and order sizes so that the profit of procurement is maximized. Assuming a finite number of scenarios exist, two-stage stochastic linear programs can be modelled as large linear programming problems. In this study various objective functions will be studied including expected profit approach and several risk averse measures.

2.1. Expected Profit Model

The following optimization model will solve the supplier selection problem (SSP) maximizing the expected profit of a risk neutral newsvendor. We refer to this problem as SSP-E.

SSP–E

Maximize $\sum_{u=1}^{U} P_u \psi_u$ (1)

Subject to

$\psi_u = (r - w)D_u - \sum_{i \in N}(c_i - w)q_i R_{iu} - (r + o - w)\zeta_u \quad u = 1, \dots, U$ (2)

$\zeta_u \geq D_u - \sum_{i \in N} q_i R_{iu} \quad u = 1, \dots, U$ (3)

$0 \leq q_i \leq K_i \quad i = 1, \dots, N$ (4)

$\zeta_u \geq 0 \quad u = 1, \dots, U$ (5)

The objective function (1) maximizes the expected profit. Constraint (2) defines the scenario profits. The amount of shortage is nonnegative and not less than the difference between the demand and the amount received from the suppliers as provided by (3). The constraint (4) ensures that the quantity received from a selected supplier cannot exceed that supplier's capacity.

In risk-neutral operating conditions firms benefit from the expected profit approach to evaluate the overall quality of the supply portfolio. On the other hand, maximizing the expected profit in the long run may result large losses in the short run and could threaten firms' financial state especially when suppliers are subject to complete disruption risks and demand is uncertain. In such situations, adopting an appropriate risk measure could be very attractive. We next review such risk measures and provide a comparative analysis in terms of their applicability on supplier selection problem and their computational efficiency.

2.2. Maximin Model

This model is used for maximizing the profit of the worst-case scenario which may occur due to a high level of mismatch between demand and supply. A decision variable, MP is defined as the minimum profit over all scenarios.

SSP–Maximin

Maximize MP (6)

Subject to $(2) - (5)$

$MP \leq \psi_u, \quad u = 1, \dots, U$ (7)

2.3. Mean-Variance Model

Markowitz's seminal work (Markowitz, 1952) is known as one of the earliest models considering the trade-off between expected return and variance of the return. We next present the of the SSP-MV model which considers this trade-off for the supplier selection problem. λ denotes the weight of the variance in the objective function (8).

SSP–MV

Maximize $\quad \sum_{u=1}^{U} P_u\psi_u - \lambda(\sum_{u=1}^{U} P_u(\psi_u)^2 - (\sum_{u=1}^{U} P_u\psi_u)^2) \quad$ (8)

Subject to $\quad$ (2) – (5)

2.4. Bounding the Profit Model

The following optimization model maximizes the expected profit among all scenarios while setting a lower bound (LB) on the profit for each scenario.

SSP–BP

Maximize $\quad$ (1)

Subject to $\quad$ (2) – (5)

$\psi_u \geq \text{LB} \qquad u = 1, \ldots, U \quad$ (9)

2.5. Stochastic *p*-Robust Model

"Stochastic *p*-robust optimization" approach maximizes the expected profit, subject to a constraint requiring the *relative regret* in any scenario to be no more than $p\%$. Let z_u be the optimal objective function value for scenario u. This value is found assuming we have perfect information that scenario u will be realized. Let AR_u be the *absolute regret* in scenario *u* that can be calculated by taking the difference between the best profit for scenario *u* if we have the perfect information that scenario *u* would occur and profit for scenario u ($AR_u = z_u - \psi_u$). Similarly *relative regret* for scenario u can also be calculated ($RR_u = AR_u/z_u$). The following formulation (SSP-p Robust) represents a Stochastic *p*-robust optimization model for a risk averse newsvendor with multiple unreliable suppliers.

SSP– *p* Robust

Maximize $\quad$ (1)

Subject to $\quad$ (2) – (5)

$\psi_u \geq (1-p)z_u \qquad u = 1, \ldots, U \quad$ (10)

A preprocessing is needed to find z_u values. For each scenario, the following optimization problem is solved (note that R_{iu} and D_u values are constants for a given scenario). In the optimal solution of this problem, the decision maker may fill the demand starting from the least-expensive supplier that is available for that scenario.

Minimize	$z_u = \sum_{i \in N} (c_i - w) q_i R_{iu}$	(11)
Subject to	(4)	
	$\sum_{i \in N} q_i \, R_{iu} = D_u$	

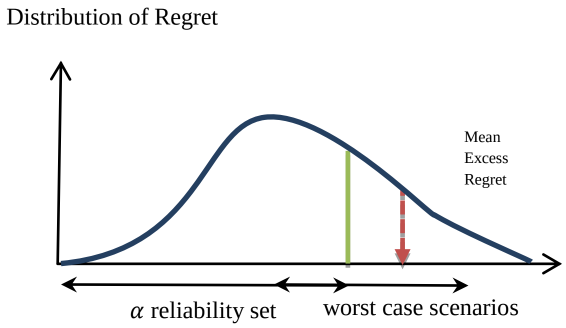
2.6. α -Reliable Minimax Regret Model

This model endogenously determine a set of "planning scenarios" whose combined probability is at least α allowing the decision maker to be 100 α % sure that the regret realized will be no more than that found by the model. In the model below (SSP–Minimax), X_u is a new binary decision variable which is 1 if the scenario u is in the planning set, it is 0 otherwise and M is a very large value. The objective function (12) minimizes the maximum regret in the planning set.

SSP–Minimax

Minimize	AR		(12)
Subject to	(2) – (5)		
	$\sum_{u=1}^{U} P_u X_u \geq \alpha$	$u = 1, \ldots, U$	(13)
	$z_u - \psi_u = AR_u$	$u = 1, \ldots, U$	(14)
	$AR_u \leq AR + M(1 - X_u)$	$u = 1, \ldots, U$	(15)
	$X_u \in \{0,1\}$	$u = 1, \ldots, U$	(16)

Figure 1. α-Reliable Mean Excess Regret



2.7. α-Reliable Mean Excess Regret Model

α-Reliable Mean Excess Regret method aims to minimize the expected regret with respect to a selected set of scenarios whose total probability is no more than 1−α

(see Figure 1). SSP-ME applies this approach to the risk averse newsvendor problem with multiple unreliable suppliers.

SSP – ME

Minimize $\zeta + (1-\alpha)^{-1} \sum_{u=1}^{U} P_u W_u$ (17)

Subject to $(2)-(5)$

$W_u \geq AR_u - \zeta \quad u = 1, \dots, U$ (18)

$W_u \geq 0 \quad u = 1, \dots, U$ (19)

Objective function (17) of the formulation above minimizes the mean excess regret. Constraint set (18) defines W_u as the tail regret for scenario u, which is the amount by which the regret in scenario u exceeds ζ. Constraint set (19) makes sure that W_u is a continuous nonnegative decision variable.

2.8. Value at Risk (VaR) Model

For a given significance value, $\alpha \in (0,1)$, the 100 α % VaR is defined as the largest value ensuring that the probability of obtaining a profit less than VaR is lower than (1- α). In other words, the VaR is the $(1-\alpha)$-quantile of the profit distribution (see Figure 2). The following optimization model (SSP-VaR) will maximize the VaR of a risk averse newsvendor problem with multiple unreliable suppliers.

SSP – VaR

Maximize VaR (20)

Subject to $(2)-(5)$

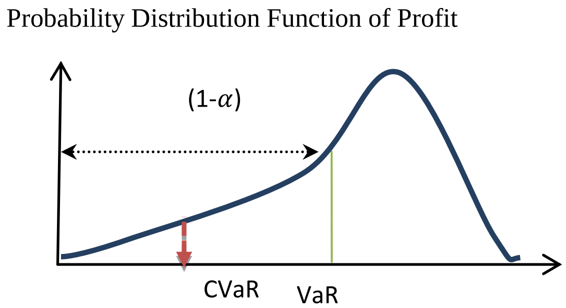
$Var - \psi_u \leq M\theta_u \quad u = 1, \dots, U$ (21)

$\sum_{u=1}^{U} P_u \theta_u \leq 1 - \alpha$ (22)

$\theta_u \in \{0,1\} \quad u = 1, \dots, U$ (23)

In the formulation above, θ_u is a binary variable and M is a large enough constant. Constraint set (21) makes sure that $\theta_u$takes the value of 1 if the profit of the scenario u is less than VaR. Constraint sets (22) and (23) ensure that the probability of obtaining a profit less than VaR is not higher than α.

Figure 2. VaR and CVaR



2.9. Conditional Value-at-Risk (CVaR) Model

CVaR is defined as the conditional expected profit given that it is less than VaR and is derived by taking a weighted average between the VaR and losses exceeding the VaR. The following optimization model (SSP-CVaR) will maximize the CVaR of a risk averse supplier selection problem. In the formulation below, the objective function (24) maximizes the CVaR where VaR is a decision variable to present VaR and α to denote the significance level for the profit distribution. Constraint set (25) defines S_u as the amount by which the profit in scenario u is short of VaR. Constraint set (26) makes sure that S_u is a continuous nonnegative decision variable.

SSP – CVaR

Maximize $\quad Var - (1-\alpha)^{-1} \sum_{u=1}^{U} P_u S_u \qquad (24)$

Subject to $\quad (2) - (5)$

$$S_u \geq Var - \psi_U \qquad u = 1, \dots, U \qquad (25)$$

$$S_u \geq 0 \qquad u = 1, \dots, U \qquad (26)$$

2.10. Analysis of the Models

The expected profit model (SSP–E) discussed in Section 3.1 focuses on the average performance of the system and assumes that decision makers are risk neutral. In many contexts, decision makers are risk averse: they are concerned not only with the expected performance, but with the potential deviation from it. This may be particularly true when managers are faced with devastating supply disruptions due to failure of the suppliers. Therefore, we formulate a number of extensions to the model that allow decision makers to explore alternate risk measures such as maximin, mean-variance, bounding the profit, stochastic p-robust, α -reliable minimax regret, value at risk (VaR) and conditional Value-at-Risk (CVaR) .

Section 3.2 presents a maximin model (SSP–Maximin) which has the advantage of not requiring scenario probabilities as inputs. However, while the expected cost measure defined in SSP–E is risk neutral, the objective of SSP–Maximin is extremely risk averse. In fact, this leads to a supplier portfolio which is frequently defined by one and possibly a very rare scenario. Such a strong aversion may result solutions with poor average performance. Therefore, it is difficult to justify focusing on the worst scenario and creating a procurement plan based on that.

The mean-variance objective (SSP-MV) discussed in Section 3.3 considers the trade-off between expected return and variance of the return. On the other hand, minimizing variance actually means equally penalizing profits that are lower than the average and higher than the average. When the objective is to maximize firm's profit penalizing higher profit values may not seem reasonable. In addition, maximizing the variance makes the problem a nonlinear programming model (NLP) while all other models considering risk are linear programming models.

Section 3.4 introduces the Bounding the profit approach (SSP-BP) that aims to set a common lower bound for the scenario profits. This approach may not make sense for problems where scenarios are significantly different from each other. It may be better to set limits for scenarios relative to the best profit that could happen for that scenario (with perfect information).

The stochastic *p*-robust optimization model (SSP– *p* Robust) revealed in Section 3.5 addresses concerns associated with the SSP-BP. This method maximizes the long-run average performance while guaranteeing acceptable performance in every scenario requiring the *relative regret* in any scenario to be no more than *p* %. On the other hand, if the regret factor *p* is reduced below a critical level, the problem may become infeasible and this is one of the main disadvantages of this model.

In real life settings, decisions are rarely taken based on the expected case or the worst case. For example, when airport capacity is designed, decision makers do not plan based on the peak demand days such as holidays. They also do not simply evaluate the average daily demand. Capacity is determined generally at a value between peak demand and average demand (Chen *et al*., 2007). Similarly, when supplier portfolio is selected, we cannot plan on the worst scenario where all suppliers disrupted and demand is at its highest level. Consider the situation where a firm has four suppliers who are subject to failures and located in different regions of the world. Although it is mathematically possible that all four fails at the same time, it is a very small possibility. Therefore taking decisions based on this extreme case may not make sense although the model in Section 3.2 advises that. In addition, we also should not equally evaluate all the scenarios (risk averse models in Section 3.3, 3.4 and 3.5). To overcome this problem we may determine a set of "planning scenarios" whose combined probability is at least α. Section 3.6, 3.7, 3.8 and 3.9 utilizes this approach.

The objective function of α -reliable Minimax Regret Model (SSP-Minimax) introduced in Section 3.6 minimizes the maximum regret in the set of "planning scenarios" whose combined probability is at least α (Daskin *et al*., 1997). On the other hand, this model could be disadvantageous as it does not asses the magnitude of the regrets that belong to worst case scenarios (the ones that are not included in the planning set). In addition, this model is mathematically difficult to solve.

In order to overcome problems associated with the Minimax Regret Model, α-Reliable Mean Excess Regret model (SSP-ME) is proposed in Section 3.7. This model minimizes the *expected regret* with respect to the set of scenarios whose total probability is no more than $1-\alpha$. According to Chen *et al*. (2007), this measure is coherent and computationally more efficient than α -reliable Minimax Regret Model.

In finance Value-at-Risk (VaR) has been a widely used risk measure for the risk of loss on a specific portfolio of financial assets. Recently VaR has also been used for non-financial applications such as supply chain risk management. In Section 3.8 we apply the VaR approach to the supplier selection problem. In the SSP – VaR model, VaR is is the $(1-\alpha)$-quantile of the profit distribution for a given a significance value $\alpha \in (0,1)$. Although VaR has been a popular risk-management tool, it is shown to be an incoherent measure lacking the sub-additivity property (Artzner *et al*. (1999)). In addition, VaR does not clarify the size of the profit when less than the VaR limit.

To overcome obstacles associated with the SSP – VaR model, Section 3.9 introduces the CVaR measure (SSP – CVaR) which is defined as the conditional expected profit given that it is less than VaR. CVaR is coherent and consistent with the second (or higher) order stochastic dominance (Artzner *et al*., 1999; Pflug, 2000; Ogryczak, Ruszczy´nski, 2002). The consistency with the stochastic dominance implies that minimizing CVaR never conflicts with maximizing the expectation of any risk averse utility function. The similarity between the CVaR and α-Reliable Mean Excess Regret methods is easy to identify. The main difference is that in the CVaR method the decision maker deals with the actual profit distribution while in the α-Reliable Mean Excess Regret method scenario based regrets are studied.

We have illustrated a broad range of strategies that decision makers might take for approaching risk in portfolio procurement models with demand uncertainty and supplier disruptions. A decision maker may choose one or more of these approaches based on firm's level of risk aversion, the flexibility of approach to fine-tune parameters, and the computational difficulty associated with each model. The analysis in this section helped us to identify α-Reliable Mean Excess Regret and CVaR as the most promising risk measures for the newsvendor problem with unreliable suppliers.

3. SUPPLY AND DEMAND SCENARIOS

The models presented in Section 3 require scenario based formulation. Each scenario specifies the supplier reliabilities together with customer demand level. If the random variable distributions for customer demand and supplier reliability factors are discrete, all possible future states can be described by a finite number of scenarios. In this case the obtained Linear Programming models in Section 3 can be solved with a low computational effort. When an appropriate solver is used, the Nonlinear Programing model in 3.3 would also not require much computational effort due to the quadratic terms in the objective function.

Supply chain disruption models often assume all-or-nothing (AON) suppliers whose reliability factors are described by Bernoulli distribution (Sawik, 2011). Once an order is placed on an AON supplier, they would either send the exact amount ordered or would not send anything at all. For this case we let ps_i be the disruption probability for supplier *i*, i.e., the parts ordered from supplier *i* are delivered without disruptions with probability $(1-ps_i)$. There will be 2^N supply scenarios when there exist *N* unreliable (AON) suppliers. In real life, the number of suppliers for a component rarely exceeds five. That is why the number of supply scenarios for AON suppliers would be quite manageable.

Demand scenarios for the models can be obtained via econometric models and expert knowledge (Hochreiter and Pflug (2007)). In this case demand distribution is assumed to be discrete and there will be *M* possible demand levels with positive probabilities. We may let pd_j be the probability that demand level is equal to D_j where $P(D = D_j) = pd_j, j = 1, \dots, M$.

When we assume that there exist AON suppliers and customer demand can be modeled with *M* discrete levels, the number of possible scenarios becomes $Mx2^N$. In this case, let $A_u$be the set of suppliers that are available for a scenario. Also assume that the customer demand for this scenario is equal to D_j. One can find the probability of such a scenario:

$$P_u = pd_j \prod_{i\in A_u}(1-ps_i) \prod_{i\in I\setminus A_u}(ps_i).$$

The probabilities above could also be modified when dependence exists among random variables. For example, supplier availabilities may be dependent because of geographic proximity, supplier commonality, etc. (Snyder, Daskin, 2007).

4. NUMERICAL STUDY

A numerical study is carried out to provide managerial insights on optimal sourcing strategies of a risk neutral (SSP-E) and risk averse decision maker (SSP-CVaR and SSP-ME). All tests were performed on a PC with an Intel Core Duo CPU, 3.20 GHz processor with 4 GB RAM. Linear Programming (LP) problems are solved using CPLEX 12.

Table 1. Parameters in the Numerical Study

Unit Revenue	r	$ 300			
Shortage Cost	e	$ 50			
Salvage Value	v	$ 50			
Significance Level	α	0.95			
Demand	D	Discrete Uniform (2,000-3,000)			
Suppliers		1	2	3	4
Unit Ordering Cost ($)	c_i	190	195	200	205
Supply Capacity	K_i	2,500	2,500	2,500	2,500
Failure Rate	ps_i	0.099	0.066	0.033	0.000001

Figure 3. Supplier Characteristics

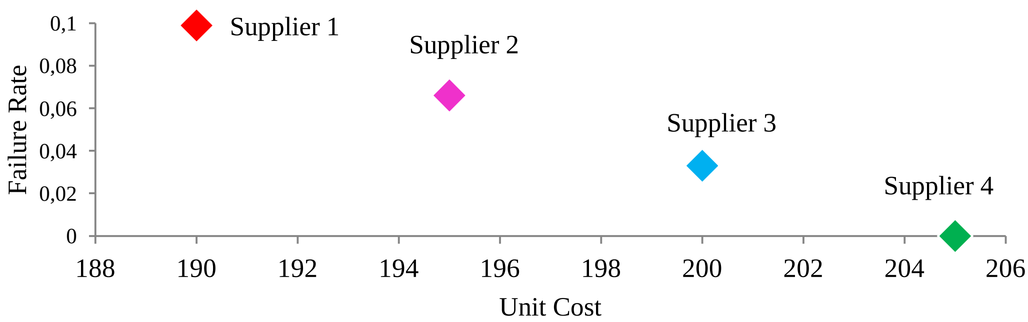


Table 1 summarizes the data used in our computational study. Customer demand is uniformly distributed between 2,000 and 3,000 (M = 1,000). Supply is provided by four All or Nothing suppliers. We assume that as supplier's unit cost decreases its failure rate increases (see Figure 3 for supplier characteristics). We have used significance level of 0.95(α) for SP-CVaR and SSP-ME models.

Table 2, Figure 4 and Figure 5 summarizes the output for the three optimization models. Solution times visibly revealed the efficiency of the scenario based LP formulations, even though number of scenarios generated were really high ($Mx2^N$ =

16,000 scenarios). According to Table 2, an instance of this size can be solved at most 4.1 seconds depending on the model type.

Table 2. Output Summaries

	SSP-E	SSP-CVaR	SSP-ME
CPU times (seconds)	1.6	3.5	4.1
Expected Profit	207,470	167,950	167,190
CVaR (α=0.95)	-4,101	166,090	112,415
Mean Excess Regret (α=0.95)	211,963	155,195	106,450
Supplier 1 Order Quantity	556	13	83
Supplier 2 Order Quantity	573	14	39
Supplier 3 Order Quantity	1,460	14	28
Supplier 4 Order Quantity	0	2,144	2,381

Figure 4. Performance Measure Summaries for Varying Models (SSP-E, SSP-CVaR, SSP-ME)

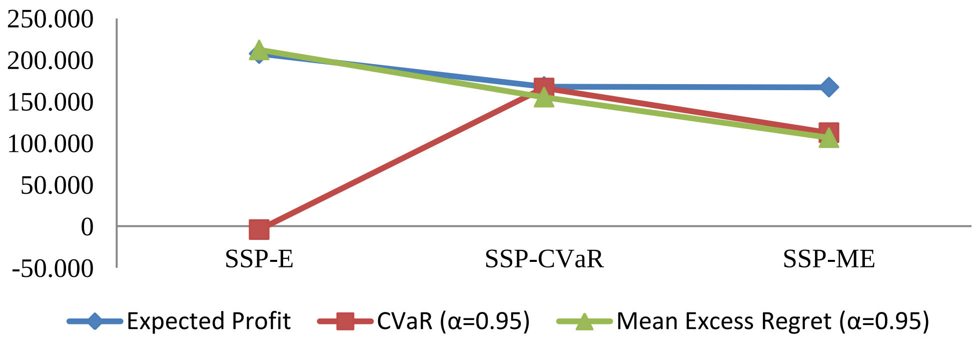


Figure 5. Order Quantities of Suppliers for Varying Models (SSP-E, SSP-CVaR, SSP-ME)

According to Table 2 and Figure 5, risk neutral decision maker only orders from low cost (but unreliable) suppliers eliminating the most secure but the most expensive supplier (Supplier 4). This result is actually in agreement with "*cost first, reliability second*" insight suggested by the risk neutral supplier selection literature.

According to Table 2 and Figure 4, when the objective is to maximize expected profit, the resulting CVaR is negative with a considerably high mean excess regret value. This result again proves that if the firm chooses to maximize the average long term profit, it may be vulnerable towards supply chain disruptions and may observe immense financial losses in the short run. On the other hand our numerical tests proved that large improvements in supply chain resilience can be attained with only small increases in the expected cost. When SSP-E and SSP-CVaR model outputs are compared, we observe a 19.05% decrease in the expected cost with a tremendous increase in the CVaR value (from -4,101 to 166,090). When SSP-E and SSP-ME model outputs are compared, we observe a 19.41 % decrease in the objective function and 49.78 % decrease in the average regret of the worst 5 % scenarios. This objective also improves the CVaR value from -4,101 to 112,415. This result actually indicates that introducing appropriate risk measures in the objective function remarkably improves the worst case scenarios and brings their average profit values close to average performance of the firm.

When we compare the SSP-CVaR and SSP-ME model outputs, we observe that expected profits do not differ much while there is a considerable difference between the optimized risk measures. For instance when SSP-ME model is employed instead of

SSP-CVaR model, expected profit decreases 0.5 % while the CVaR value and the mean excess regret values both decrease around 32 %.

4.1. Effect of Significance Level

Table 3 provides summary of our observations regarding SSP-CVaR and SSP-ME models for varying significance levels. It is observed that solutions divert from the risk neutral case as the significance level increases gets closer to one. Note that when the significance level is zero, these models are same as the expected profit model. Figure 6, Figure 7 and Figure 8 helps the reader to visualize the results presented in Table 3.

Table 3. SSP-ME and SSP-CVaR Models for Varying Significance Levels

	0	0.01	0.10	0.25	0.50	0.85	0.95	0.99
	SSP-CVaR							
Expected Profit	207,470	207,460	206,770	203,280	193,860	175,090	167,950	164,950
S1 Order Quantity	556	548	451	290	131	38	13	3
S2 Order Quantity	573	565	467	303	138	40	14	3
S 3 Order Quantity	1,460	1,471	485	317	145	42	14	3
S4 Order Quantity	0	0	1,134	1,551	1,938	2,101	2,144	2,162
								SSP-ME
Expected Profit	207,470	207,440	206,940	204,470	196,050	175,200	167,190	163,720
S1 Order Quantity	556	558	501	407	285	127	83	62
S2 Order Quantity	573	570	510	409	269	88	39	16
S 3 Order Quantity	1,460	1,378	551	422	272	83	28	6
S4 Order Quantity	0	83	1,020	1,333	1,730	2,239	2,381	2,444

Test results summarized by Table 3, Figure 6 and Figure 7 clearly indicated that risk adversity greatly influences the supplier portfolio selection decisions of firms. It is mainly due to the fact that risk averse decision maker would like to improve the performance of the worst possible set of scenarios by mostly procuring mostly from the most reliable but expensive supplier (Supplier 4). As the risk adversity level decreases, order quantities from other suppliers with lower cost and reliabilities increase. On the other hand, it is very interesting to observe that SSP-CVaR model still recommends to order some quantity from Supplier 4 even at a very low significance level (0.01).

According to Figure 8, as the significance level increases, average long term performance of the firm worsens for both SSP-CVaR or SSP-ME models. It is interesting to note that expected profit levels resulted from these two approaches do not differ substantially for the same value of significance levels.

Figure 6. Order Quantities of Suppliers for SSP-ME Model with Varying Significance Values

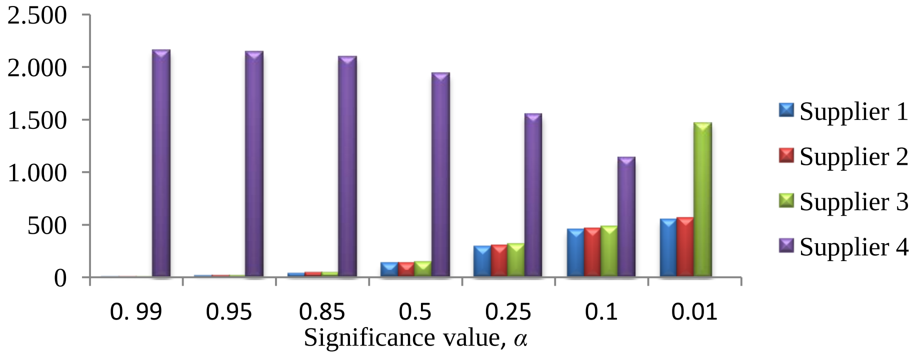


Figure 7. Order Quantities of Suppliers for SSP-CVaR Model with Varying Significance Values

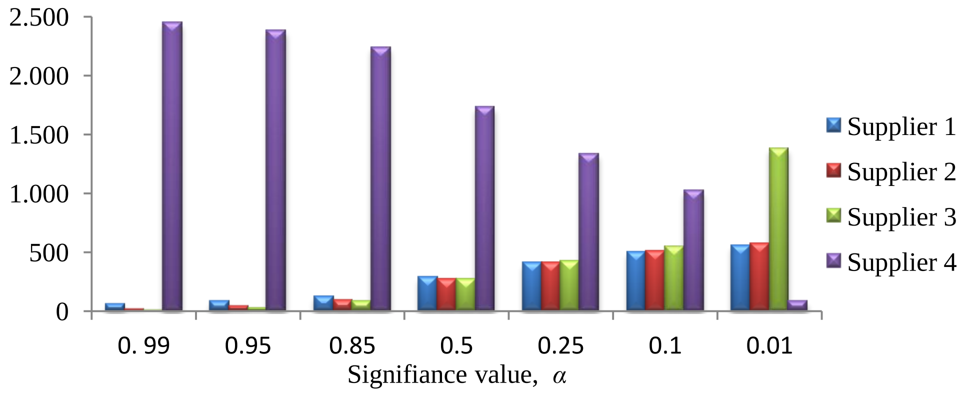


Figure 8. Expected Profit for SSP-ME and SSP-CVaR Models with Varying Significance Values

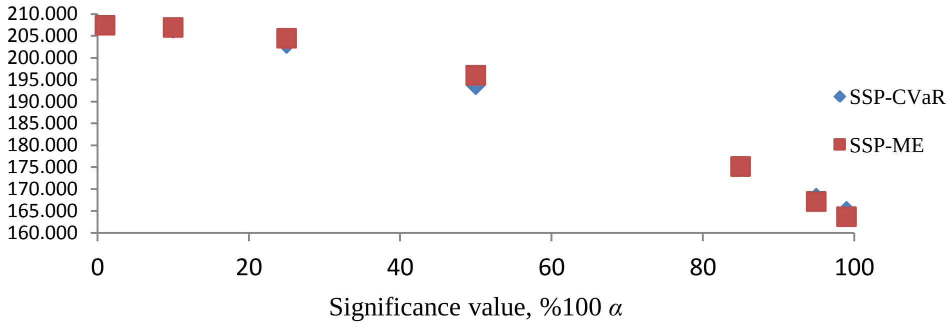


Table 4: SSP-E and SSP-CVaR models for varying unit revenue

	300	350	400	450	500
	SSP-CVaR				
Expected Profit	167,950	273,010	377,530	481,420	585,060
S1 Order Quantity	13	8	5	4	3
S2 Order Quantity	14	8	6	4	3
S 3 Order Quantity	14	9	6	4	3
S4 Order Quantity	2,144	2,140	2,134	2,127	2,121
					SSP-E
Expected Profit	207,470	325,390	445,200	566,240	688,070
S1 Order Quantity	556	462	388	337	304
S2 Order Quantity	573	471	392	338	304
S 3 Order Quantity	1,460	482	396	339	304
S4 Order Quantity	0	1,231	1,512	1,708	1,838

4.2. Effect of Unit Revenue

To study the effect of unit revenue in the model, we employed five different levels: \$300 (base), \$350, \$400, 450 and \$500. In order to simplify our analysis, we only considered SSP-CVaR model to reflect the risk averse decision maker's perspective. Table 4, Figure 9, Figure 10 and Figure 11 outline results of this sensitivity analysis. According to Figure 9, expected profit increases with increasing unit revenue for both risk averse and risk neutral models. Our results also show that the impact of the unit revenue is more evident in the risk neutral supplier portfolio. According to Figure 11, as unit revenue increases, a risk neutral firm increases its order quantity from Supplier 4 which is the most expensive but dependable supplier compared to the other suppliers in the set. This is due to the fact that when unit revenue is very high, lost sales could lead scenarios with low profits (or loss). The decision maker aims to eliminate such scenarios as much as possible by increasing its order from the low-risk supplier. Therefore, we may conclude that in the presence of high unit revenue (and high cost of lost sales) optimal supplier portfolio of a risk neutral firm becomes similar to the one of a risk averse firm. Higher unit revenue results higher total order quantities for the SSP-E model as oppose to SSP-CVaR model.

Figure 9. Expected Profit for SSP-E and SSP-CVaR Models with Varying Unit Revenues

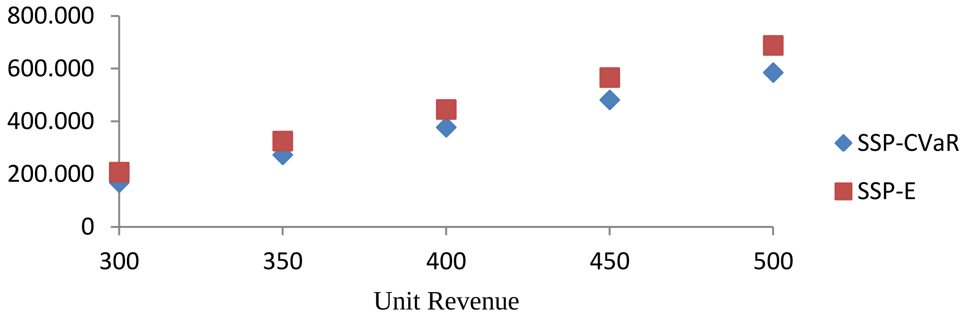


Figure 10. Order Quantities of Suppliers for SSP-CVaR Model with Varying Unit Revenues

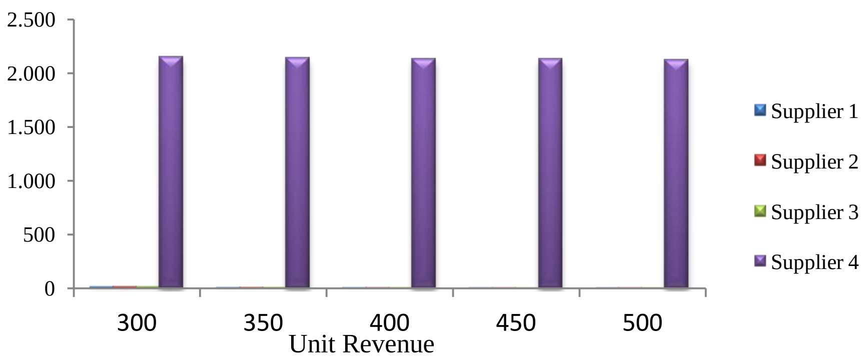


Figure 11. Order Quantities of Suppliers for SSP-E Model with Varying Unit Revenues

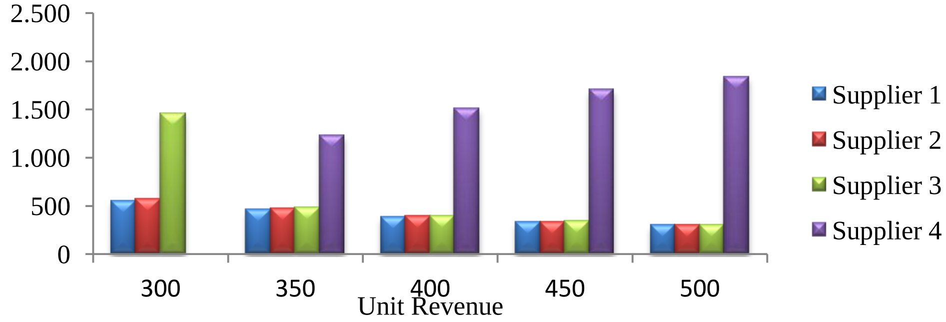


Table 5. SSP-E and SSP-CVaR Models for Varying unit Lost sale Penalty

	50	100	150	200	250
	SSP-CVaR				
Expected Profit	167,950	150,820	137,930	127,890	119,750
S1 Order Quantity	13	14	14	14	13
S2 Order Quantity	14	15	15	14	13
S 3 Order Quantity	14	15	15	14	14
S4 Order Quantity	2,144	2,257	2,345	2,416	2,472
					SSP-E
Expected Profit	207,470	200,420	195,250	191,310	188,170
S1 Order Quantity	556	462	388	337	304
S2 Order Quantity	573	471	392	338	304
S 3 Order Quantity	1,460	482	396	339	304
S4 Order Quantity	0	1,231	1,512	1,708	1,838

4.3. Effect of Lost Sale Penalty

We examined five different levels of lost sale penalty, 50 (base), 100, 150, 200 and 250. Table 5, Figure 12, Figure 13 and Figure 14 summarizes the results of this sensitivity analysis. According to Figure 12, as lost sale penalty increases, expected profit decreases for both models while this decrease is more evident for the risk averse case (29% versus 9.30%). It is easy to see that increasing lost sale penalty and increasing unit revenue have the same effect on the risk neutral objective function coefficients. Figure 11 and Figure 14 clearly indicate this result.

Table 5 and Figure 13 revealed that increasing lost sale penalty is not same as increasing unit revenue for the risk averse model. For this model, total order quantity (and supplier 4's order quantity) increases with higher lost sale penalties as opposed to observed decrease in such values.

Figure 12. Expected Profit for SSP-E and SSP-CVaR Models with Varying Lost Sale Penalties

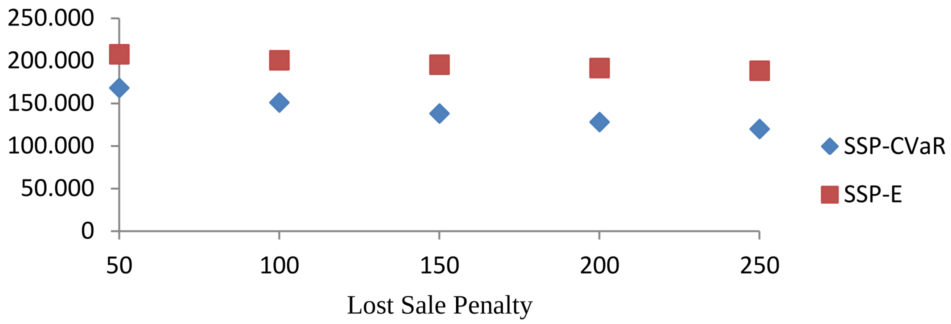


Figure 13. Order Quantities of Suppliers for SSP-CVaR Model with Varying Lost Sale Penalties

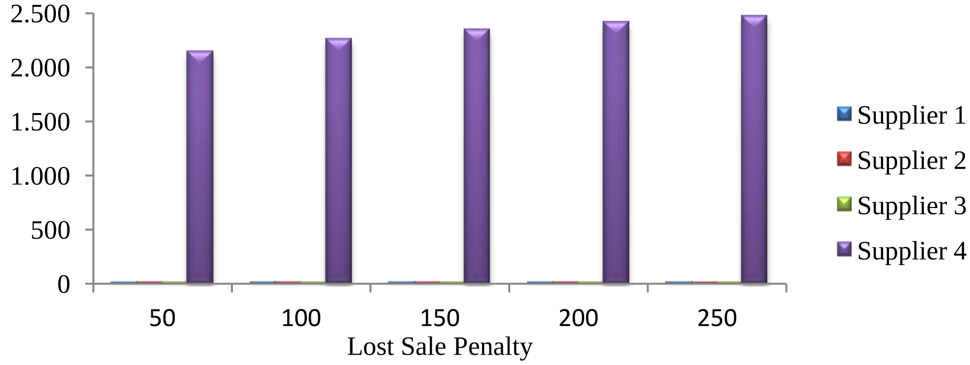
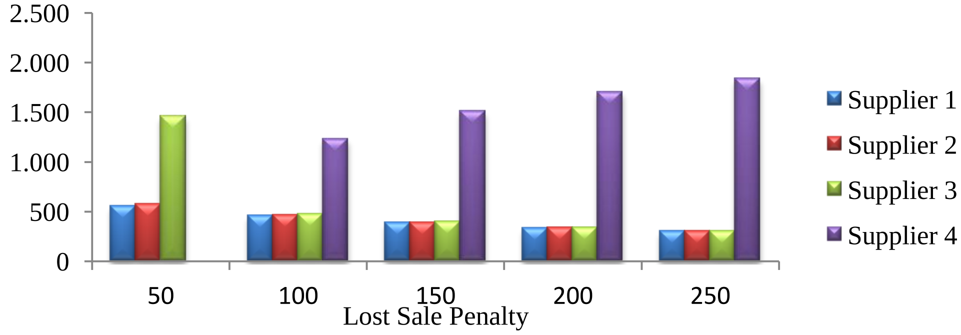


Figure 14. Order Quantities of Suppliers for SSP-E Model with Varying Lost sale Penalties



CONCLUSION

In this paper, we present various optimization models for resilient supplier selection decisions in a newsvendor setting. In this framework, the decision maker first identifies future scenarios and estimates the probability of each scenario occurring. We provided Linear Programming formulations for the scenario-based optimization problems. Such models can be easily solved using commercially available software even the number of scenarios is very large. This study also carried out a numerical study to describe optimal sourcing behaviors of risk averse and risk neutral firms. In the numerical study, CVaR and Mean Excess Regret models are selected for evaluation. Our results indicated that as the firm becomes more risk averse, the worst case scenarios improve and move closer to the average performance; on the other hand this approach also deteriorates the average performance of the firm. A potential direction for future research is to consider the effects of varying distributions for customer demand and supplier reliabilities. There could also be dependences among supplier reliabilities and customer demand, studying such effects would also be interesting.

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