A stochastic simulation-based holistic evaluation approach with DEA for vendor selection

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\textbf{A B S T R A C T}

This paper aims to propose a new vendor evaluation framework by incorporating stochastic discrete event simulation and data envelopment analysis (DEA) approaches. The proposed approach enables the assessment of decision-making units (DMUs) in a holistic manner by adopting a simulation scheme and defining DMUs not as individual vendors, but as entire supply chains. Extensive experimental results show that the efficiency of a supply chain is not critically proportional to the efficiencies of individual suppliers. Moreover, procurement performance depends on the harmonious performance of the entire supply chain that includes vendors, procurement structure, ordering and safety stock policy of buyer, and demand variability rather than each supplier’s performance.

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\section{1. Introduction}

The recent global supply chains are severely affected by a variety of risk factors, such as natural disaster, information infrastructure breakdown, labor dispute, war and terrorism, exchange rate variability, supplier bankruptcy, and so on, as structural, economic, and social complexity are increased (Chopra and Sodhi, 2012). Four main factors affect the supply chain risk (Aqil and Lam, 2015): the structural complexity of the supply chain composed of procurement, manufacturing, distribution, and market; intensified competition between global supply chains; strongly correlated economies among countries; and unexpected occurrences of disasters or events. Such risk has been managed in four perspectives, supply, product, information, and demand (Tang, 2006). Among them, the supply management is the most important one to the long-term performance of supply chain because it determines the structure of the supply chain (Braglia and Petroni, 2000; Wu and Blackhurst, 2009).

Vendor selection, an essential activity of the supply management, is for a buyer to select a combination of suppliers and to allocate proper order quantities to the selected vendors under consideration of capacity, service, lead time, and unit price (He et al., 2008). An appropriate vendor selection enables to mitigate various risks by providing an adequate level of service to the customer at the lowest cost (Tang, 2006; Wu and Blackhurst, 2009). Additionally, it can improve financial outcomes by increasing the entire supply chain’s competitive advantage (Choi and Hartley, 1996) and enables it to provide new services to the customer based on improved cost structure (Wu and Olson, 2008).

Many methodologies have been proposed to solve the vendor selection problem, such as Mathematical Programming, Analytic Hierarchy Process, Case-Based Reasoning, and Data Envelopment Analysis (DEA) (Ho et al., 2010). Among them, the DEA is the most popular approach for the problem. The DEA can measure relative efficiencies for each entity that is a so-called decision-making unit (DMU). It has been successfully applied to an assessment of DMUs that have multiple inputs and outputs with a mixture of quantitative and qualitative variables and unknown transformation function (Wong and Wong, 2007). A supply chain composed of interconnected participants has a high structural complexity and various operating policies. Therefore, it is very hard to derive an exact mathematical transformation function of it (Azadeh et al., 2016a). Moreover, the inputs and outputs of DMUs for the vendor selection are usually multiple, even worse, some of them are qualitatively like as quality, performance, technology, or information system (Pang and Bai, 2013). These reasons make the DEA as the most popular approach for the vendor selection (Weber et al., 1991). Conventional DEAs for the vendor selection, however, have two main drawbacks. First, existing DEAs consider only suppliers as DMUs. The initiative of the supply chain management is that high performance in participants does not guarantee high performance in the entire supply chain. The supply chain’s performance and

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risk can be improved when harmony occurs among the participants. Second, most previous DEAs for the vendor selection consider the inputs and the outputs to be deterministic; consequently, the relative efficiencies of DMUs are also deterministic. Those are indeed, random variables with uncertainty in practice. If the supply chain risk is one of the purposes, it should be moreover. The factors frequently vary according to their business environment. Thus, the most efficient vendor at a time can become inefficient in another situation. Although several research works have dealt with this uncertainty (Wu and Olson, 2008; Talluri et al., 2006; Talluri and Narasimhan, 2003), to our best knowledge in the vendor selection, no DEA approach handles the entire supply chain with uncertainty.

This paper, with these considerations, suggests a new stochastic simulation-based DEA approach to the vendor selection problem, in which a DMU is assigned as a supply chain instead of an individual vendor. The proposed approach also enables the evaluation of DMUs in a realistic way, with the adoption of a stochastic simulation scheme, and simultaneously helps the purchaser choose a proper set of vendors with a holistic perspective. Manuj and Mentzer (2008) pointed out that supply chain risk can be dealt with in three perspectives, supply, demand, and operation. We also retain such respect in this research. In the stochastic discrete event simulation, we consider vendor characteristics such as price, quality, delivery, and procurement structure; demand variation such as demand size and variant; and operational policy such as inventory and order quantity policies. A simple supply chain is considered to illustrate the simulation consisting of customer, retailer, and vendors. We conducted extensive simulations for various scenarios to obtain sufficient sampled data and applied deterministic input-oriented DEA with the samples to analyze the stochastic nature of the efficiencies.

We organized the rest of the paper as follows: Section 2 summarizes related work, and Section 3 details the considered supply chain model. After describing the experimental design in Section 4, extensive simulation results and analyses are presented in Section 5. Finally, Section 6 concludes this work.

2. Literature review

Significant studies have been made on the vendor selection with DEA. Narasimhan et al. (2001) proposed a modified DEA approach. Using technical efficiencies via a typical DEA and managerial performance ratings, they categorize suppliers into four groups: high performers and efficient (HE), high performers and inefficient (HI), low performers and efficient (LE), and low performers and inefficient (LI). Here, the DMUs in the HE are considered as benchmarks for other groups to improve their performances. Wong and Wong (2007) have proposed two DEA models to evaluate internal supply chain performance, from technical and cost-efficiency perspectives. They have claimed that information from the DEA models enables managers to identify inefficient operations and establish efficient resource planning. Ha and Krishnan (2008) proposed a mixed vendor evaluation method, using AHP for quantitative variables, and DEA and neural networks for qualitative variables. Wu and Blackhurst (2009) have focused on the unrestricted weight flexibility problem, which is a weakness of the DEA. They inserted an ideal DMU into a set of existing DMUs, and employed a cross-evaluation matrix in the work of Sexton et al. (1986) and super-efficiency of Andersen and Petersen (1993) to overcome the weakness. The works of Ho et al. (2010) and Azadeh et al. (2016b) provide further research on DEA approach in the field of vendor selection.

To deal with uncertainty, Talluri and Narasimhan (2003) introduced a max-min DEA approach. The basic concept of it involves adding a new ideal DMU and obtaining a range between the maximum relative efficiency and the minimum relative efficiency, in which the optimal solutions can be calculated by setting the objective to maximize or to minimize in the DEA’s linear programming (LP) formulation. Talluri et al. (2006) have proposed a chance constrained DEA that solves chance-constrained programming rather than the LP to calculate the relative efficiencies of DMUs with variability. Wu and Olson (2008) introduced a DEA incorporating a Monte Carlo simulation. The method regards some of the DMUs’ input and output variables as random variables and generates values following a specific distribution. A deterministic DEA is then performed to obtain the DMUs’ relative efficiency.

In the case of imprecise and uncertain data, Fuzzy DEA (Pang and Bai, 2013; Haq and Kannan, 2006; Yang et al., 2008) using the fuzzy set theory is pervasive. There are four types of Fuzzy DEA (Hatami-Marbini et al., 2011), the tolerance approach, the α-based approach, the fuzzy ranking approach, and the possibility approach. The most popular one for vendor selection is α-based approach that converts a fuzzy programming into several interval programming (Azadeh and Alem, 2010). Recently, Azadeh et al. (2016b) proposed a decision-making procedure of an appropriate DEA for vendor selection, in which one of the DEA, Fuzzy DEA, or Stochastic DEA is selected according to the crispness of data and availability of sufficient historical data. Azadeh et al. (2011) also introduced an approach that integrates fuzzy simulation and Fuzzy DEA to determine efficient process layout with ambiguous processing times. Its procedure is similar to our approach, but the application is different.

Above stochastic DEA and Fuzzy DEA studies concentrated on overcoming the uncertainty and imprecise data weaknesses of typical DEA. However, the methods consider only vendors, so some limitation exists in reflecting the harmony of the supplier, demand, and operational policies. Moreover, those requiring additional information or assumptions, such as a joint probability density function, accurate transformation function, fuzzy numbers, and normality assumption. Obtaining and satisfying those are sometimes impossible or cumbersome.

Simulation is the most prominent approach to consider the interaction and conflict quantitative and qualitative factors of highly complex real-world supply chains. Recently, Azadeh et al. (2016b) have proposed an integrated vendor allocation approach of simulation, DEA, and Taguchi method to maximize the gained benefit and the number of high-quality products for closed loop supply chains that consider both forward and reverse flows simultaneously. It is noteworthy that this paper simulates the actual situation carefully by considering product’s life cycle, customer behavior, quality of raw materials and final products, transportation time, and policies for returned products. The basic idea of this paper is similar to our study by sequentially applying simulation and DEA. However, this paper aims at the optimal supply chain operation that determines the optimal order quantities for vendors under a given supply chain structure. On the other hand, our study focuses on the optimal supply chain design that determines the optimal supply chain structure and the internal operation policy regarding risk and efficiency.

In current DEA, it is very hard to analyze the internal participant’s effects because it regards a DMU as a “black box.” A new DEA method, so-called “network” DEA approach, has been proposed to overcome the structural weakness. The approach separates a DMU into sub-DMUs and calculates product flows between the sub-DMUs. Lewis and Sexton (2004) have introduced the network DEA method based on an example of a major league baseball team. Tone and Tsutsui (2008) have introduced a slack-based network DEA model, where the relative efficiencies of a DMU and its sub-DMUs are evaluated simultaneously. The results illustrated that the network DEA approach is superior to find accurate relative efficiencies of a DMU and its sub-DMUs, rather than the pre-
vicious black box typed DEA. Cook et al. (2010) have developed a DEA approach for a supply chain with intervened inputs and outputs. Chen and Yan (2011) have proposed DEA models with centralized, decentralized, and mixed decision maker. Although these network DEA methods are advantageous to assess structural efficiency, they are still insufficient to satisfy our purpose. The approaches can handle only simple structure such as a two-echelon model with a buyer and two suppliers and product flows in assembly perspective due to computational complexity. Moreover, they still suffer from employing uncertainties.

3. Procurement structures

The vendor selection problem involves determining a set of suppliers to maximize the purchaser’s profit. Here, the selection implies not only choosing suppliers from the whole set but also deciding a procurement structure. A well-designed procurement system not only can improve the performance but also can reduce risk of a supply chain. Our proposed approach achieves this purpose by adopting simulation and considering a supply chain as an entity in the DEA method. We introduce three procurement models in this perspective; single vendor, dual vendors with an emergency order, and dual vendors with demand splitting, as illustrated in Fig. 1.

The single vendor model (PS-S) consists of three types of participants, a vendor, a retailer, and a customer. The vendor characterizes by unit cost (UCV), the retailer’s purchasing cost per unit), lead time (LTv), and coefficient of variation (CV) of lead time (CVLTv). The retailer has its operational policies on economic order quantity (EOQv), reorder point (ROPv), and safety stock (SSv) by

\[ \text{EOQv} = \sqrt{\frac{2D_v C_v}{h_v}} \]

\[ \text{ROPv} = D_v LT_v + SS_v - LQ_v \]

\[ SS_v = \Phi^{-1}(pc) \sqrt{LT_v \sigma^2_{LT_v} + D^2 \sigma^2_{LT_v}} \]

Here, \( D_v \) denote the amount of daily demand. We assume that the \( D_v \) follows a Normal distribution with the mean \( \mu_{D_v} \) and the variance \( \sigma^2_{D_v} \), i.e., \( N(\mu_{D_v}, \sigma^2_{D_v}) \). \( h_v \) represents the ordering cost per order and the unit holding cost per day of the retailer, respectively. \( LQ_v \) is defined as the amount of purchase orders that are already released and are expected to be arriving in \( LT_v \). \( SS_v \) denote the quantity of the safety stock. \( pc \) denote a desired customer service level, and \( \sigma^2_{LT_v} \) is the variance of the \( LT_v \). \( \Phi^{-1}(\cdot) \) is the inverse distribution function of a standard Normal distribution.

In the dual vendors with emergency order model (PS-DE) (Moinzadeh and Nahmias, 1988), a major supplier (Vendor 1) is in charge of ordinary orders, and a standby supplier (Vendor 2) covers emergency orders. The retailer pays a higher \( UC_v \) for the order with urgent in requisit of a shorter \( LT_v \). Therefore, the supplier with a longer \( LT_v \) becomes the major supplier and the other becomes standby supplier, i.e., \( LT_{V1} \geq LT_{V2} \). If both vendors have the same \( LT_v \), the vendor with a large CVLTv is chosen for the major because the vendor with a large CVLTv gives lower \( UC_v \). If the vendor has larger CVLTv and higher \( UC_v \), the vendor will be removed from candidates of vendors. The candidate vendors should have trade-offs among \( UC_v \), \( LT_v \), and \( CVLT_v \). The retailer determines the amount of the ordinary order and reorder point as \( EOQ_{V1} \) and \( ROP_{V1} \), respectively by Eq. (2). An emergency order only occurs when the ordinary order is expected not to retain the inventory level. Since the emergency order should be arrived before the arrival of the imminent ordinary order, \( LQ_v \) for emergency order becomes zero. Thus, the emergency order quantity \( OQ_{V1} \) and reorder point \( ROP_{V1} \) are calculated by Eq. (2), where \( l \) denotes current inventory level and \( RL_{V1} \) represents remaining expected lead time for the imminent ordinary order.

\[ \text{EOQ}_{V1} = \sqrt{\frac{2D_v C_v}{h_v}} \]

\[ \text{ROP}_{V1} = D_v LT_{V1} + SS_{V1} - LQ_{V1} \]

\[ SS_{V1} = \Phi^{-1}(pc) \sqrt{LT_{V1} \sigma^2_{LT_{V1}} + D^2 \sigma^2_{LT_{V1}}} \]

The last model is the dual vendors with demand splitting model (PS-DS) (Zhao and Lau, 1992; Lau and Lau, 1994). In this model, the economic order quantity and reorder point are the same to the PS-S, but a demand is evenly distributed to each vendor. Therefore, \( EOQ_v \) for each vendor is calculated with the half of daily demand. \( LQ_{V1} \) and \( LQ_{V2} \) denote the order quantities arrived from both vendors in \( LT_{V1} \) and \( LT_{V2} \), respectively.

\[ \text{EOQ}_{V1} = \sqrt{\frac{2(0.5D_v C_v)}{h_v}} \]

\[ \text{ROP}_{V1} = D_v LT_{V1} + SS_{V1} - LQ_{V1} \]

\[ \text{EOQ}_{V2} = \sqrt{\frac{2(0.5D_v C_v)}{h_v}} \]

\[ \text{ROP}_{V2} = D_v LT_{V2} + SS_{V2} - LQ_{V2} \]

\[ SS_{V1} = \Phi^{-1}(pc) \sqrt{LT_{V1} \sigma^2_{LT_{V1}} + (0.5D)^2 \sigma^2_{LT_{V1}}} \]

\[ SS_{V2} = \Phi^{-1}(pc) \sqrt{LT_{V2} \sigma^2_{LT_{V2}} + (0.5D)^2 \sigma^2_{LT_{V2}}} \]
4. Simulation-based DEA for vendor selection

4.1. Framework of the proposed approach

This section provides an overview of our proposed approach incorporating the discrete event simulation and the DEA. Fig. 2 illustrates the brief procedure. At the first stage, we conduct discrete event simulations for 200 DMUs (20 PS-Ss, 90 PS-DEs, and 90 PS-DSs) under six circumstances (three demands and two holding costs). We explain the numbers in Section 4.3. Since the simulation continues for 100 years and the data is aggregated for every year, total 200,000 sets of inputs and outputs are generated. Then, at the second stage, we run a deterministic DEA with the data to obtain relative efficiencies for the 20,000 inputs (200 DMUs and 100 simulation results for each DMU). This framework provides four advantages. First, the inputs and outputs for DEA already include uncertainties by adopting discrete event simulation. Second, our approach enables to deal with the vendor selection problem in a holistic perspective because we consider a DMU as a supply chain that has specified procurement structure and operational policies. Third, since our approach evaluates sufficient numbers of DMUs, the DEA can maintain the discrimination power for technical efficiency. Fourth, the DEA provides 100 sampled efficiencies for each DMU, so statistical analyses are possible.

4.2. Discrete event simulation

For the discrete event simulation, following assumptions are prerequisite:
• All demands and incoming deliveries arrive at the beginning of the day.
• All customer demands deliver at the end of the day.
• The retailer knows the average and the CV for the lead time of all vendors.
• Partial delivery is not permitted for all orders and demands
• All unsatisfied demands are backordered.

By the assumptions, we can build the discrete event simulation in a supply chain as shown in Fig. 1. We provided a pseudo-code for the PS-DE only, but others can be constructed easily. In the pseudo-code, \( O_{i,j} \), \( ELT_{i,j} \), and \( ALT_{i,j} \) denote the order quantity, the expected lead time, and the actual lead time of the \( j \)th vendor at the \( j \)th time period, respectively. We assume that \( ELT_{i,j} \) is the same to average lead time of \( V_i \) and \( ALT_{i,j} \) is generated by a Lognormal distribution \( LN(ELT_{i,j}, \sigma^{2}_{ALT_{i,j}}) \) when the \( O_{i,j} \) is released. To reduce the output variance, a common random number (CRN) is used for the simulation to generate daily demands and actual lead time for each procurement structure (Kleijnen, 1992). The warming-up length set to 60 days to eliminate the effect of initial values. Every year, we saved several system performance metrics, such as daily total cost (dollars/day), maximum inventory level (units), fill rate, and on-time delivery rate by conducting intensive simulations with diverse scenarios. We coded the algorithm using R Ver. 3.3.0 and performed the simulation on Intel i5-5200U 2.2GHz with 8GB memory.

4.3. Scenarios and parameters

Extensive simulations have been conducted with various procurement scenarios. Those are several combinations of vendor structure, safety stock level, retailer purchasing policy, demand distribution, holding cost, and vendor characteristics. The details of the simulation parameter settings are as follows.

First, as explained earlier, we adopted the three procurement structures. We also considered two safety stock policies, no safety stock (SSP-Z) and safety stock with 0.99 customer service level (SSP-0.99), as noted in Table 1. Any additional procurement structures and safety stock policies can be applied without any change in the experiment’s structure.

Other parameter settings in Eqs. (1)–(3) for simulations are demonstrated in Table 2, where \( \rho_{Dc} \) denotes a CV of demands and \( b_k \) denotes a backordering cost of the retailer.

We consider ten vendors as noted in Table 3, with different averages and CV of lead time for the simulation. A vendor with a higher purchasing cost has a short lead time and a small CV. Conversely, lower purchasing cost leads long lead time and higher CV. If two vendors have the same average of lead time, then the one with a smaller CV has a higher purchasing cost.
4.4. DEA

To obtain technical efficiencies of the DMUs, we applied an input-oriented constant return to scale DEA (Cooper et al., 2011). As a DEA with uncertainty, we can also consider a stochastic DEA, chance-constrained DEA, or Fuzzy DEA. To apply these methodologies, however, we need to know an exact transformation function, joint distribution function, or normality assumption. A realistic supply chain, especially, if it has a complicated structure and operational policies as our model, it is hard to meet those assumptions. In this case, the conventional deterministic DEA is more helpful than these DEAs due to its flexibility. Moreover, since our approach already secures sufficient sampled data throughout the extensive discrete event simulation, additional stochastic DEA is redundant for our case. We employed “Benchmarking” Package Ver. 0.26 (Bogetoft and Otto, 2015) in R under the constant return to scale and input-oriented technical efficiency.

We selected the total cost and the maximum inventory (required storage space) of the whole supply chain as input factors for the DEA, and the fill rate and the on-time delivery rate as the outputs. The proposed DEA model evaluates 200 DMUs (for 100 times each) to select the best procurement structure simultaneously. Table 4 lists all 200 DMUs considered in this research. The first twenty DMUs (DMU 1 to 20) represent PS-Ss with SSP-Z policy and SSP-0.99 respectively. The DMUs from 21 to 110 have a PS-DE. Among them, the first 45 DMUs (DMU 21 to 65) have the SSP-Z policy, and the next 45 DMUs (DMU 66 to 110) have the SSP-0.99. The composition order of the dual vendors is (1,2), (1,3), (1,4), …

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### Table 4

| Decision-making unit list. |  |

<table>
<thead>
<tr>
<th>Procurement structure</th>
<th>Safety stock policy</th>
<th>DMU</th>
</tr>
</thead>
<tbody>
<tr>
<td>PS-S</td>
<td>SSP-Z</td>
<td>1–10</td>
</tr>
<tr>
<td>PS-DE</td>
<td>SSP-0.99</td>
<td>11–20</td>
</tr>
<tr>
<td>PS-DS</td>
<td>SSP-Z</td>
<td>21–65</td>
</tr>
<tr>
<td>PS-DS</td>
<td>SSP-0.99</td>
<td>66–110</td>
</tr>
<tr>
<td>PS-DS</td>
<td>SSP-Z</td>
<td>111–155</td>
</tr>
<tr>
<td>PS-DS</td>
<td>SSP-0.99</td>
<td>156–200</td>
</tr>
</tbody>
</table>

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Fig. 3. Pseudo-code for the discrete event simulation of the PS-DE.
Fig. 4. Technical efficiencies of each DMU for $\rho_D = 0.05$ and $h_R = 0.005$.

Fig. 5. Technical efficiencies of each DMU for $\rho_D = 0.05$ and $h_R = 0.05$.

(5,6), (5,7), (5,8), ••• (8,10), (9,10). A vendor with a shorter lead time is assigned to one for an emergency order. Similarly, the last 90 DMUs (DMU 111 to 200) represent the PS-DS with the SSP-2 and the SSP-0.99.

5. Experimental results

5.1. Overall disposition

In this section, we analyze several DEA results to validate the effectiveness of our approach. Figs 4–9 plot technical efficiencies for each DMU according to $\rho_D$, and $h_R$. Note that each DMU has 100 efficiencies due to the discrete event simulation. We highlighted the average, the minimum, and the maximum of the efficiencies for each DMU to investigate overall efficiency and robustness.

The Figs 4–9 show following two implications. First, high demand variability leads significant variation in efficiency of DMUs. In the Figs 4–9, the variance of efficiencies for a DMU increase as the CV of demand under the same holding cost. Second, the effect of the holding cost differs as the CV of demand. The larger holding cost increases the efficiency variation in $\rho_D = 0.75$, while de-
increases in $\rho_{DC} = 0.05$ and 0.25. These results imply that the CV of demand and the holding cost should be considered simultaneously to select appropriate supplier.

5.2. Vendor selection without risk measure

In a long-term decision making or risk insensitive case, efficient DMUs can be determined only based on their average efficiency. Table 5 lists top 20 efficient DMUs and their average technical efficiencies. Values in bold denote the most efficient DMU in each scenario. Now, we investigate in detail the effects of each factor.

5.2.1. Effect of holding cost

A large holding cost results in a short ordering interval and a small order quantity. In Table 5, the number of efficient DMUs using the safety stock (column SSP-0.99) at $h_R = 0.05$ is bigger than one at $h_R = 0.005$. This implies that the safety stock increases the efficiency of DMUs in large holding cost. If the variation of demand is not large enough, i.e., $\rho_{DC} = 0.05$ and 0.25, the most efficient DMU is one of PS-S and SSP-Z. On the other hand, if the demand variation is large, the most efficient DMU has dual vendors structure. When $h_R = 0.005$, Vendor 10 (DMU 10) that has the lowest $UC_V$ is the most efficient. If $h_R = 0.05$, Vendor 8 (DMU 8) with a rel-

Fig. 6. Technical efficiencies of each DMU for $\rho_{DC} = 0.25$ and $h_R = 0.005$.

Fig. 7. Technical efficiencies of each DMU for $\rho_{DC} = 0.25$ and $h_R = 0.05$. 
5.2.2. Effect of CV of demand

If the CV of demand is large, the PS-DE is superior to other procurement structures. At $\rho_D = 0.75$, the most efficient DMU changes into PS-DE from PS-S. In this case, if the holding cost of the retailer is small, the supply chain with PS-DE and no safety stock policy (PSS-2) is preferred, otherwise PS-DE and some safety stock (PSS-0.99) is preferred. A high holding cost leads frequent small sized orders, and consequently the low inventory level. Thus, the supply chain is vulnerable to variation of demand. In this case, some safety stock is helpful to increase the performance of the supply chain. Therefore, the CV of demand is a critical factor should be considered to determine an efficient procurement structure and operational policies of a supply chain.

5.2.3. Procurement structure selection

The PS-S is useful for stable demand, the PS-DE is favorable for rapid demand variation, and the PS-DS is advantageous for keeping relatively high $UC_V$ and short $LT_V$ becomes the most efficient DMU. In summary, the holding cost could be a critical factor in determining a procurement structure and safety stock policy. Simultaneously, it affects to efficiency for the same procurement structure.
low inventory level, respectively. We present some guidelines to utilize the procurement structures.

If a retailer prefers a PS-S, it can select an appropriate vendor based on the business environment and its operational policies. If the demand is stable and customer service level is not critical, the vendors with low $UCV$ such as Vendor 10 or 8 are advantages in spite of large lead time. Otherwise, the vendors having a small lead time variability such as Vendor 5 could be the best. If dual vendors are available, the PS-DE guarantee a high performance for large variation of demand by compensating weaknesses each other. The advantage of the PS-DS is a low inventory level due to alternating orders, so the structure is suitable where the holding cost is high or, the production volume is big. The PS-DS, however, is inefficient if demand varies in large range and holding cost is low.

5.3. Vendor selection with risk measure

In short-term or medium-term vendor selections, the performance of a supply chain can be more sensitive to the risk of the stochastic uncertainties. Krokhmal et al. (2002) applied various risk measures such as Conditional Value-at-Risk (CVaR), value-at-risk (VaR), conditional drawdown-at-risk (CDaR), mean-absolute deviation (MAD), and maximum risk of their portfolio management problem. In the risk-sensitive case, DEA results can be dealt with risk measures such as standard deviation, variance, MAD, lower-

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### Table 5
Top 20 average efficiency DMUs for CV of demand and holding cost.

<table>
<thead>
<tr>
<th>$\rho_{DE}$</th>
<th>$\bar{h}_{T}$</th>
<th>Procurement structure and safety stock policy</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>$\text{SSP-Z}$</td>
</tr>
<tr>
<td>0.05</td>
<td>0.005</td>
<td>5 (0.99)</td>
</tr>
<tr>
<td>0.05</td>
<td>0.005</td>
<td>8 (1)</td>
</tr>
<tr>
<td>0.25</td>
<td>0.005</td>
<td>10 (0.99)</td>
</tr>
<tr>
<td>0.05</td>
<td>0.005</td>
<td>8 (1)</td>
</tr>
<tr>
<td>0.75</td>
<td>0.005</td>
<td>10 (0.94)</td>
</tr>
<tr>
<td>0.05</td>
<td>0.005</td>
<td>5 (0.99)</td>
</tr>
<tr>
<td>0.75</td>
<td>0.005</td>
<td>8 (0.94)</td>
</tr>
<tr>
<td>0.05</td>
<td>0.005</td>
<td>7 (0.94)</td>
</tr>
</tbody>
</table>

* DMUs in bold denote the most efficient DMU in average for each scenario.
semi absolute deviation, VaR, CVar, CDaR, maximum risk, and so on. One of strengths of this approach is that more than one risk measures can be utilized at the same time according to decision makers’ purpose. The risk of each simulation result is defined as 1-technical efficiency in order to make the amount of the risk positive. In this section, the VaR_{95\%} is used for an example of risk measures. VaR_{(1−\alpha)} is the maximum risk with a given \((1−\alpha) \times 100\%\) confidence level, over a given time period (Hull, 2014). VaR can be defined as follows:

\[
VaR_{(1−\alpha)} = \inf\{x \in R : P(1 − F > x) \leq \alpha\},
\]

where F is technical efficiency. VaR_{95\%} represents the minimum risk from worst 5% simulation results for same DMU. Table 6 lists top 20 efficient DMUs and their average technical efficiencies with 1 - VaR_{95\%} ≥ 0.9.

The most efficient DMU in Tables 5 and 6 are exactly same. When \(\rho_D=0.05\) or \(\rho_D=0.25\) and \(h_R=0.005\) the top 20 DMUs are same in Tables 5 and 6, which means to use the VaR_{95\%} constraint does not give any effects on. When \(\rho_D=0.25\) and \(h_R=0.05\), 7–5 (SSP-0.99, PS-DS) in Table 5 is not shown in Table 6, then 10–7 (SSP-Z, PS-DS) enters the top 20 DMUs instead. When the demand is stable (\(\rho_D=0.05\) or 0.25) or, the risk constraint has almost no impact on the top 20 DMUs selection. In these cases, DMUs for higher technical efficiency presents lower risk. However, when the demand is not stable (\(\rho_D=0.75\)) only 16 DMUs shown in Table 6. All other DMUs for \(\rho_D=0.75\) are out of the constraint. Therefore, decision makers need carefully to consider the risk when the demand is not stable. For more conservative decision, a decision maker can use more conservative constraints such as maximum risk ≤0.1 or VaR_{99\%} ≤ 0.1 or smaller right-hand side of the constraint such as VaR_{95\%} ≤ 0.05.

### 6. Conclusion

This study proposes a new vendor evaluation method by incorporating simulation and DEA. The proposed approach has the following features: First, as the proposed method adopts a stochastic simulation scheme, it can consider uncertainties in the real world. Second, this approach evaluates vendors based on the performances of the entire supply chains including procurement structures and operational policies. The method, with these two features, provides a holistic vendor evaluation process. Obviously, with this procedure, more complicated and realistic supply chains can be considered by elaborating the simulation model. Therefore, future work will apply the proposed approach to various vendor selection problems, and advance the proposed simulation model.

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