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Improved Acquisition for System Sustainment: Resilience-Based Supplier Selection for Maintenance, Repair, and Overhaul Acquisition

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Improved Acquisition for System Sustainment: Resilience-Based Supplier Selection for Maintenance, Repair, and Overhaul Acquisition

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Abstract

The occurrence of disruptive events, whether attacks, natural disasters, accidents, or common failures, is inevitable. As such, risk-based planning across many domains has focused on *resilience*, or the ability to withstand and recover from such disruptions. Resilience should be an important criterion when choosing suppliers. This report describes a research effort that is framed around improving supplier selection by integrating several dimensions of supplier alternatives under uncertainty, primarily focusing on supplier resilience. This work (i) explored a set of supplier selection criteria that includes accounting for resilience measures, and (ii) developed a means to compare probability distributions with an initial application in project management risk (with an application in supplier selection still on-going). This research serves a greater public good in studying supply chains that the public relies upon for daily life, and the methodologies and insights provided in this work can be applicable to a broad range of systems whose supply chains are subject to disruption. Selecting suppliers that are more insulated to these disruptions and understanding how supply chain designs affect resilience is paramount across many applications.

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1. INTRODUCTION

Supply chain management is becoming increasingly significant to achieve competitiveness in the business environment, as recently the paradigm for corporate management has shifted from competition between individual firms to the competition between supply chains [Cho et al. 2008]. In supply chain management, relationships with suppliers have an impact on the success of the strategic goals of a buyer. Hence, it is necessary for a buyer to keep track of these relationships and evaluate supplier performance and optimize its supply base.

Manufacturing companies need to collaborate with various suppliers to continue their business activities. In manufacturing industries, raw materials and component parts can amount to 70% of the cost of a finished product [Stueland 2004]. In such a circumstance, the acquisition department can have a significant influence on cost reduction, suggesting that supplier selection is among the more critical functions of acquisition.

Supplier evaluation and selection is the process of finding a capable supplier that is able to supply high quality products at the right time at the right price. Supplier selection is a multi-criteria decision making problem that involves two major tasks: (i) determine criteria to be considered, and (ii) compare the eligibility of suppliers. Generally speaking, the traditional criteria associated with supplier selection can be divided qualitative and quantitative categories. Quantitative supplier criteria have included transportation costs, purchasing and order costs, delivery time, and product defect rate, while qualitative criteria have included product quality, warranties and claim policies, performance history, technical capability, geographical location, and labor relations [Luo et al. 2009, Liao and Kao 2011, Arikan 2013, Lienland et al. 2013, Yu and Wong 2015].

Although research efforts have been dedicated to supplier evaluation and selection, accounting for resilience-based criteria for supplier selection have not been well explored. The notion of resilience, or the ability of a company or its supply chain to withstand and subsequently recover from a disruption, has become very important in the scope of supply chain management. Supplier disruptions can impose significant losses to the entire supply chain by discontinuing of supply flows. For example, a devastating earthquake in central Taiwan in September 1999 had severe consequences for many manufacturing industries and organizations, as total industrial production losses were approximated at $1.2 billion [Papadakis 2006]. Many large scale semiconductor fabrication facilities, estimated to account for roughly 10% of the world's production of computer memory chips, were damaged [Bhamra et al. 2011]. The impact of earthquake disaster on PC supply chain was dramatic, as the supply of computer components was constrained for several months, affecting technology companies such as Dell, Gateway, IBM, Apple, and HP.

In 2011, the Japanese earthquake and tsunami had similar adverse impacts to the global supply chain networks of automobile manufacturers [Manual 2013]. For example, automobile manufacturers attempted to find other sources for a special pigment used in automobile paint after the Japanese earthquake and tsunami disabled the main facility in 2011. The availability of new US automobiles was reduced for several months after the disruption of key suppliers, including the paint supplier. Availability is a key metric not only in industry but also in the DoD. Weapons system availability is critical to the DoD [2005], requiring that such systems be operational at a moment's notice. With smaller maintenance, repair, and overhaul (MRO) inventories and as modern supply chains are increasingly vulnerable to disruptions, it is important to understand how *resilient* suppliers are to such disruptions so that system availability can be maintained.

While other work has analyzed supply chain resilience [e.g., Sheffi 2005, Tang 2006, Petit et al. 2010, Carvalho et al. 2012], the *objective of this research* was to develop and deploy a framework for supplier selection under uncertainty with multiple criteria, including specific consideration for supply chain resilience.

2. Background

This section provides methodological background to some components of this research, including a paradigm for resilience, recent approaches to comparing suppliers, and a particular approach for the multi-criteria comparison of discrete alternatives.

2.1. Resilience Modeling

In the last few years, the concept of *resilience* has been increasingly used to describe the behavior of systems under disruption, and several measures of resilience have been offered [Park et al. 2013, Hosseini et al. 2016]. In particular, this work adopts a graphical paradigm of system behavior before, during, and after a disruption is provided in Figure 1 [Henry and Ramirez-Marquez 2012, Barker et al. 2013, Pant et al. 2014]. It is assumed that system performance, measured with function $\varphi(t)$, reduces after a disruptive event e^k and improves to an acceptable level over time (e.g., flow along a network, availability of a system or supply chain). Figure 1 highlights three dimensions of resilience: reliability, vulnerability, and recoverability. The normal behavior of the system in the time interval $t_\mathrm{e} - t_0$, or in its *Stable Original State*, S_0, is described by the system's reliability. The vulnerability dimension of resilience describes the extent to which $\varphi(t)$ degrades to a *Disrupted State*, S_d, during the time interval $t_\mathrm{d} - t_\mathrm{e}$. The recovery of the system to its *Stable Recovered State*, S_f, occurs during the time interval $t_\mathrm{f} - t_\mathrm{d}$.

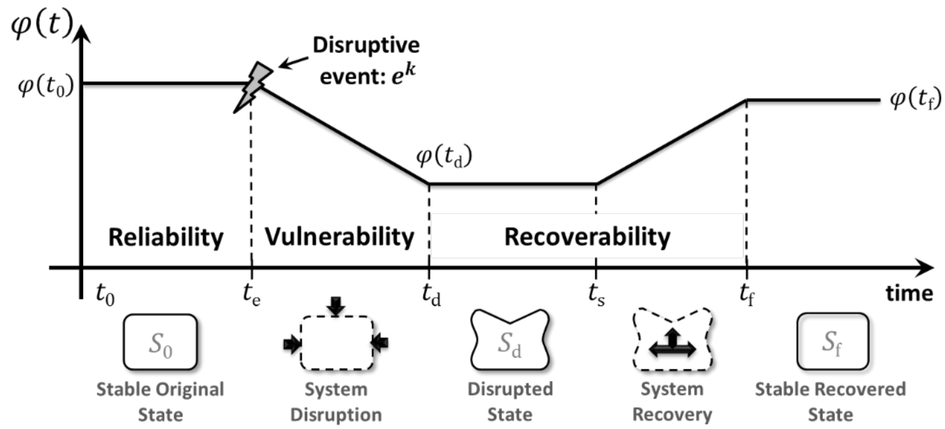

Figure 1. Graphical depiction of system performance, $\varphi(t)$, across several state transitions over time.

2.2. Supplier Selection Approaches

Various methods have been implemented to deal with supplier selection problem including multi-criteria decision analysis techniques, mathematical programming, and artificial intelligence, among others. Liao and Kao [2011] combined a fuzzy extension of TOPSIS and multi-choice goal programming to solve the supplier selection problem, allowing a decision maker to consider multiple aspiration levels. Kilincci and Onal [2011] employed fuzzy extension of the analytic hierarchy process (AHP) for supplier selection. Karsak and Dursun [2014] introduced an approach based on integrating quality function deployment and data envelopment analysis for selecting the best among supplier alternatives, studying the interdependence among supplier evaluation criteria with the construction of a house of quality. Deng and Chen [2011] proposed a methodology based on fuzzy set theory and Dempster-Shafer theory to deal with the supplier selection problem. Igoulalene et al. [2015] proposed a fuzzy hybrid multi-criteria decision analysis approach based on combining fuzzy consensus-based possibly measure and fuzzy TOPSIS. Kar [2014] integrated fuzzy AHP and fuzzy goal programming for the supplier selection problem. Lee et al. [2014] combined TOPSIS and AHP based on fuzzy theory to determine the prior weights of criteria and select the best-fit suppliers by taking subjective vague preferences of decision making into account. You et al. [2015] developed a new multi-criteria decision model based on using interval 2-tuple linguistic variables and an extended VIKOR approach to select the best supplier under uncertainty and incomplete information. Dalalah et al. [2011] adjusted DEMATEL to deal with fuzzy rating and assessments by converting the relationship between causes and effect of the criteria into an intelligible structural model. Deng et al. [2014] presented a new form of representation for uncertain information involved with supplier selection, called D numbers, which the authors then integrated with AHP. Fazlollahtabar et al. [2011] proposed a multiobjective mixed integer programming for supplier selection with an objective to minimize total supplier costs including cost, total defect rate, total penalized earliness and tardiness, and total value of purchase.

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3. Supplier Selection Criteria

Dickson [1966] introduced 23 supplier selection criteria still found in literature today, including quality, delivery, performance history, and price.

3.1. Availability Criterion

The performance function for a supply chain, $\varphi(t) = A_0(t)$, is assumed to be its *availability,* measured as a proportional level of service (ratio of uptime to total time) that can be attained by the products produced by a supply chain. This work makes use of a formulation by Sherbrooke [2004] (and extended computationally by Nowicki et al. [2012]) to redistribute supplies coming from a number of suppliers in meeting demand in a multi-echelon supply chain.

An example is provided in Figure 2, where the supply chain has a central depot, two intermediate locations (e.g., end-item integrators), and six field locations (e.g., sub-assembly suppliers). Each location within an echelon has an input vector that defines the cost, reliability, and maintainability of a spare item at that location. The item's reliability is defined in terms of average number of demands per year, and the item's maintainability is defined as mean time to repair in days. Availability measure A_0, as well as the associated spare strategy for each supplier, was obtained from the algorithm described in Nowicki et al. [2012]. The objective of the algorithm is to determine the vendor mix and quantity of spares that either maximizes the operational availability subject to a budget constraint (or otherwise minimizes cost subject to an operational availability target).

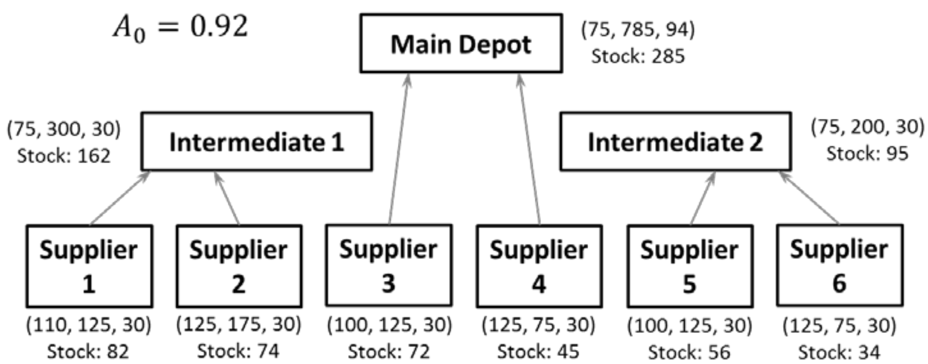

Figure 2. Supply chain topology and characteristics resulting in an availability of 0.92.

Let E represent the set of echelons in a multi-echelon supply chain, with $e = 0,1,\dots,|E|$. Let L^e be the set of locations within e, with index $l = 1,2,\dots,|L^e|$, and let I^{le} be the set of items at location l within echelon e. As the index of an item or product is i, the demand quantity of item i at location l within echelon e in any fixed interval of length t is $N_i^{le}(t)$. And s_i^{le} represents the stock level of item i at location l within echelon e.

To calculate the availability of the multi-echelon supply chain, the expected number of backorders must be identified as the expected amount of unfilled demand that exists at a point in time. Note that unfilled demand is a function of a particular delay scenario, and as such, depends on the number of existing spares at each location within each echelon they can be used as a surrogate measure for operational availability. Therefore, the amount of backorders for item i can be calculated with Eq. (1) [Nowicki et al. 2012].

$$BO\left(N_i^{le}(t)\middle|s_i^{le}\right) = \begin{cases} N_i^{le}(t) & \text{if } N_i^{le}(t) > s_i^{le} \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

Note that a backorder of size $N_i^{le}(t) - s_i^{le}$ occurs whenever the number of demands exceeds the inventory on-hand, or $N_i^{le}(t) > s_i^{le}$. As such, the expected number of backorder can be calculated with Eq. (2), where x is the random variable.

$$E\left[BO\left(N_i^{le}(t)\middle|s_i^{le}\right)\right] = \sum_{x=s_i^{le}+1}^{\infty} \left(x - s_i^{le}\right) P\left[N_i^{le}(t) = x\right] \tag{2}$$

Finally, Shebrooke [2004] demonstrated that the availability of a multi-echelon supply chain denoted by A_0 system can be calculated with Eq. (3).

$$A_0 = 100 \prod_{l=1}^{L^E} \prod_{i=1}^{I^{lE}} \left(1 - E\left[BO\left(N_i^{le}(t)\middle|s_i^{le}\right)\right]/n\right)^n \tag{3}$$

In this study, we would like to identify a backup supplier who can improve the availability of supply chain when a primary supplier is disrupted. As such, a more resilient supply chain would be able to rebound to an availability value similar to (or improved relative to) baseline availability performance in a timely fashion.

3.2. Recovery Time, Quality, and Delivery Rate Criteria

In addition to the availability measure, other criteria are used to compare suppliers. Pairing with availability is *recovery time*, or the amount of time taken to engage an alternative supplier to improve availability. Hence, a supplier with a shorter recovery time (measured in days) is more desirable because it contributes to a more resilient supply chain when combined with availability. The logic behind the combination behind vulnerability and recoverability, as a function of availability, is illustrated in Figure 3. Again, $\varphi(t)$ is represented with the availability measure from Eq. (3).

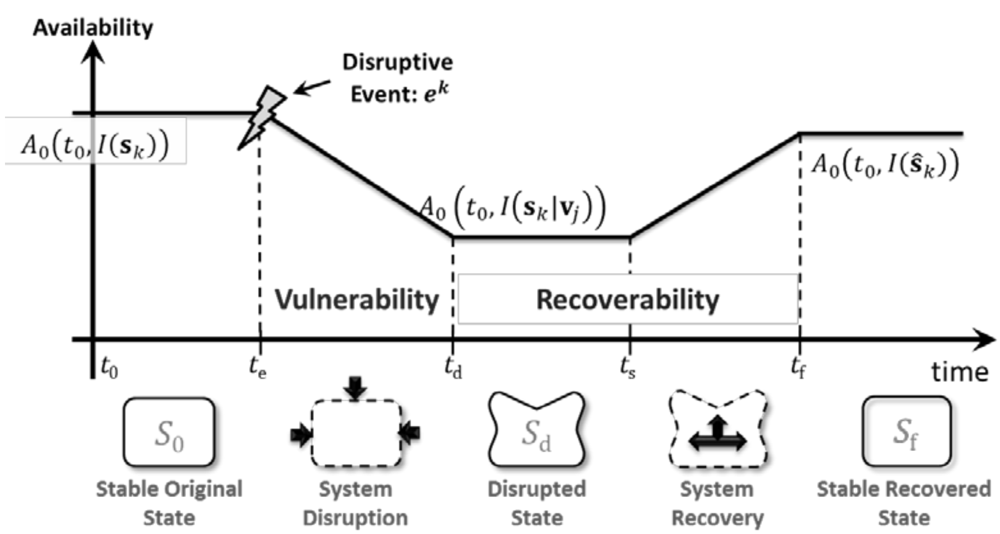

Figure 3. Graphical depiction of availability over time after a disruption to a supplier.

The ability to meet specifications consistently is referred to as *quality*, and a commonly used criterion in supplier evaluation. The quality of the product, process, or system is defined here as the percentage of products that meet the expectations of manufacturers. Dickson [1966] defines *delivery rate* as the percentage of successful delivery to meet specified delivery schedules. Its meaning is extended into criteria such as freight terms, lead time, delivery capacity, shipment quality, cycle time, and JIT delivery capability.

Availability, recovery time, quality, and delivery rate criteria are integrated together using TOPSIS for the comparison of suppliers that can be engaged when a primary is disrupted. This idea is illustrated with an example in the next section.

3.3. TOPSIS

TOPSIS was developed by Hwang and Yoon (1981) for finding the best among several discrete alternatives given multiple decision criteria. The basic principle of TOPSIS is that the chosen alternative should be the closest to the best (or positive ideal) solution and farthest from the worst (or negative ideal) solution. Suppose that there are *n* criteria $(C_1, \dots, C_n)$ which are considered to discern among m discrete alternatives $(A_1, \dots, A_m)$. Let x_{ij} be the performance of the ith alternative for the jth criterion. The weight of importance of the jth criterion is w_j, such that $\sum_{j=1}^{n} w_j = 1$. TOPSIS is applied to rank the m alternatives with six steps as follows.

Step 1. Calculate the normalized value n_{ij} for $i = 1, \dots, m$ and $j = 1, \dots, n$. Eq. (4) represents one such approach to normalizing the value of the criteria (which could be of different magnitudes) for each alternative.

$$n_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \tag{4}$$

Step 2. Calculate the weighted normalized value v_{ij} with Eq. (5).

$$v_{ij} = w_j n_{ij} \tag{5}$$

Step 3. Determine the positive ideal solution A^+ and the negative ideal solution A^- with Eqs. (6) and (7), where S_B and S_C denote the set of benefit criteria and set of cost criteria, respectively. The positive ideal solution has all the best attainable criteria values, while the negative ideal solution has all worst possible criteria values.

Eq. (6) suggests that the positive ideal solution consists of those weighted performance ratings that maximize benefit criteria and minimize cost criteria. Likewise, the negative ideal solution, or the weighted performance ratings that represent the smallest from set S_B and largest from set S_C, is provided in Eq. (7).

$$A^+ = \{v_1^+, \dots, v_n^+\} = \left\{\left(\max_i v_{ij} \mid j \in S_B\right), \left(\min_i v_{ij} \mid j \in S_C\right)\right\} \tag{6}$$

$$A^- = \{v_1^-, \dots, v_n^-\} = \left\{\left(\min_i v_{ij} \mid j \in S_B\right), \left(\max_i v_{ij} \mid j \in S_C\right)\right\} \tag{7}$$

Step 4. Calculate Euclidean distance between each alternative and the positive and negative ideal solutions with Eqs. (8) and (9), respectively, for all i.

$$S_i^+ = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j^+\right)^2} \tag{8}$$

$$S_i^- = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j^-\right)^2} \tag{9}$$

Step 5. Calculate the relative closeness to the ideal solution, for all i.

$$RC_i = \frac{S_i^-}{S_i^+ + S_i^-} \tag{10}$$

Step 6. Rank the alternatives according to RC_i in Eq. (10). The larger the value of RC_i, the closer alternative i is to the positive ideal solution. As such, alternatives are ranked according to descending values of RC_i.

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4. Illustrative Example

An example of a three-echelon supply chain of spares illustrates the availability and other criteria to evaluate and compare suppliers. Figure 2 illustrates the baseline supply chain configuration with the stock of spares assigned in each of the echelons.

Recall that each location within an echelon has an input vector that defines the cost, reliability (average demand per year), and maintainability (mean time to repair in days) of spare items at that location. In Figure 2, suppliers 1 and 2 and suppliers 5 and 6 supply to intermediate depot locations, while suppliers 3 and 4 supply to the main depot location. Note that the availability of the spares supply chain is calculated using Eq. (3). More information about how the availability of multi-echelon can be calculated can be found in Sherbrooke [2004].

It is assumed that supplier 1 is disrupted and becomes inoperable, as illustrated in Figure 4. The availability reduces from 0.92 to 0.80.

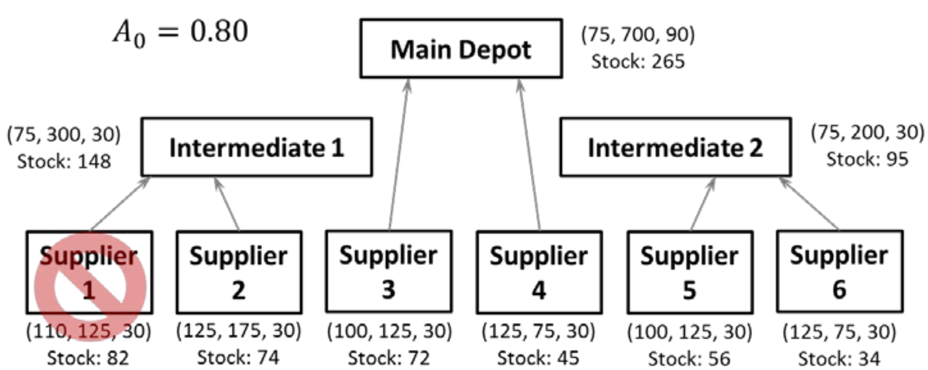

Figure 4. Availability reduction when supplier 1 becomes inoperable.

Assume that three suppliers (A, B, and C) are evaluated as replacements for supplier 1. When their cost, reliability, and maintainability information are individually inserted in the availability algorithm, the supply chain availability resulting from alternative suppliers A, B, and C are 0.95, 0.92, and 0.90, respectively. These availability values, as well as the values of the quality, delivery, and recovery time criteria, are found in Table 1. Figure 5 provides an illustration of the resilience, or the combination of availability improvement and recovery time, of the three suppliers.

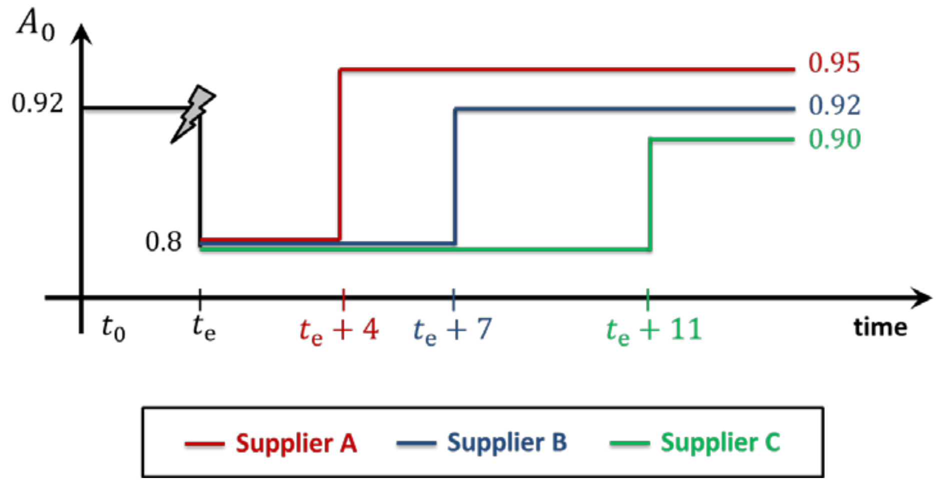

Figure 5. Depiction of the contributions of the three alternative suppliers to supply chain resilience.

Table 1. Criteria values for the three alternative suppliers to replace supplier 1.

	Availability improvement	Recovery time	Quality	Delivery rate
Supplier A	0.15	4	0.97	0.82
Supplier B	0.12	7	0.83	0.98
Supplier C	0.1	11	0.89	0.91

Criteria weights of $\mathbf{w} = [0.3, 0.3, 0.2, 0.2]$ are assumed for availability improvement, recovery time, quality, and delivery rate, respectively. The integration of the four criteria and their weights using TOPSIS results in the ranking provided in Table 2. A such, supplier A would be the best fit to replace supplier 1 in the event that supplier 1 becomes inoperable, according to the four criteria and how those criteria are weighted.

Table 2. Closeness coefficient and rank for each of the alternative suppliers.

Alternative supplier	RC_i	Rank
Supplier A	0.8934	1
Supplier B	0.5693	2
Supplier C	0.1074	3

4.1. Ongoing Work

We are still exploring (i) computational aspects of calculating availability for multiple suppliers, and (ii) the sensitivity of supplier selection to the weights assigned to supplier selection. We present a decision support idea for this approach in the next section, with application to project risk.

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5. Comparing Alternatives under Uncertainty

Understanding that many of the parameters used in the comparison of supplier alternatives are estimated by previous observations or expert evidence, or otherwise may be described by uncertain values, the supplier selection framework must account for uncertainty. We first explored this idea in the context of project risk, with an application to supplier selection still ongoing.

To quantify project risk, we adopt the risk triplet combination of scenario, likelihood, and consequence [Kaplan and Garrick 1981, Pfeifer et al. 2015]. A *scenario* represents a disruption to a project task or set of tasks, the *consequence* of which is defined as the amount of delay in project completion time. As task completion times and, thus, project completion time are likely random variables, there exists a *likelihood* of the delay in project completion time. Mitigating project risk could involve allocating more resources (e.g., labor, equipment) than originally planned to ensure tasks are completed timely [Kessler and Chakrabarti 1999].

As such, it is important to identify the tasks that are the primary sources of project risk, thus on which mitigation efforts should be placed. When task completion times are assumed to be deterministic, the critical path method (CPM) is often used to determine which tasks that, when delayed, lead to a delay in the completion time of the project. However, as task completion times are uncertain, or at least assumed to follow a distribution with known parameters, CPM has been extended to allow for random task completion times with the program evaluation and review technique (PERT).

We propose an alternative approach to identifying risky project tasks with a decision analysis technique applied to stochastic ranking. We compare the completion time distributions resulting from different task delays with a TOPSIS. Doing so allows for the comparison of the entirety of the distribution of project completion time, potentially emphasizing the extremes of the distribution [Asbeck and Haimes 1984, Lambert et al. 1994, Frohwein et al. 1999] (e.g., a delay in a particular task may have a low likelihood of a short project delay but a high likelihood of a lengthy project delay). Although PERT does allow for consideration of the worst-case task completion time scenario, it does not allow an emphasis on the worst-case scenario in identifying project risk. An overview of the four steps in the approach is given in Figure 6. This same idea could be applied to any of the criteria in the supplier selection problem.

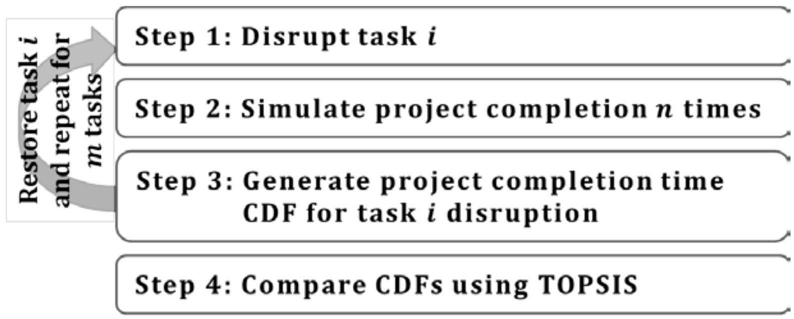


Figure 6. Overview of the four steps of the proposed approach for identifying tasks that lead to project risk.

Assume a project network as a connected set of m nodes, representing project tasks, and links, representing the precedence relationship among those tasks.

In the first step of the approach, task i is chosen from the network and is disrupted. That is, its completion time distribution is altered, depending on the nature of the distribution. For example, if a task completion time is assumed to follow a normal distribution, perhaps mean completion time is delayed by some amount y. For task completion times following a triangular distribution, perhaps the minimum, most likely, and maximum parameters of the distribution are all delayed by y time units.

In the second step, project completion time is simulated with realizations of task completion times using PERT and Monte Carlo simulation. This results in n realizations of project completion time resulting from delayed task i and all other tasks at their baseline completion time distribution. In the third step, a cumulative distribution function (CDF) is generated for the project completion time associated with a delay in task i. The completion time distribution for task i is then restored to its baseline level, and step 1 is repeated until all m tasks have been individually delayed and m project completion time distributions have been collected.

Finally, in the fourth step, TOPSIS is used to perform stochastic ranking of the task delays, accounting for the entirety of the distribution and its extremes. This comparison is generally shown in Figure 7 for the completion time of two delayed tasks. Criteria weights can be applied to emphasize particular percentiles of the CDF (e.g., the median 50th percentile, the worst-case 90th percentile).

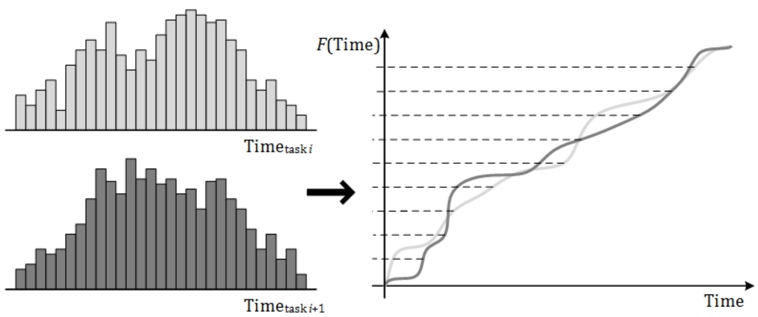


Figure 7. Comparison of project completion time distributions resulting from delays in tasks i and $i+1$ (adapted from Rocco et al. [2015]).

5.1. An Illustration: 36 Tasks, One Critical Path

The project network depicted in Figure 8 has 36 tasks [Tolentino Pena 2009]. The completion time for each task is assumed to follow a triangular distribution, the parameters for which are provided in Table . There are 40 paths between tasks 1 and 36, but this network contains only one critical path, which is shown in Figure 8 with bolded precedence links and in Table with bolded task numbers.

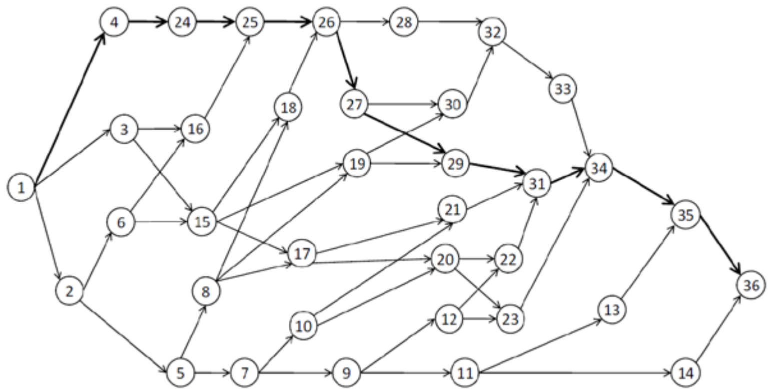


Figure 8. Illustrative example 1 of 36 tasks with a single critical path emphasized with bolded precedence links (adapted from Tolentino Pena [2009]).

Table 3. Parameters of the triangular distributions of task completion times for example 1, tasks on the critical path bolded.

Task	Min	Mode	Max	Task	Min	Mode	Max
1	**20**	**30**	**40**	19	4	6	8
2	1	2	3	20	3	6	8
3	2	5	9	21	1	4	7
4	**22**	**24**	**26**	22	3	5	7
5	1	4	8	23	2	5	9
6	1	5	8	**24**	**24**	**28**	**32**
7	2	3	5	**25**	**22**	**28**	**40**
8	4	6	9	**26**	**20**	**30**	**40**
9	1	3	6	**27**	**18**	**22**	**26**
10	1	2	3	28	3	5	6
11	3	6	10	**29**	**28**	**35**	**42**
12	3	6	10	30	5	6	8
13	1	5	7	**31**	**20**	**30**	**40**
14	1	4	6	32	1	4	6
15	4	6	8	33	5	6	7
16	8	10	12	**34**	**25**	**30**	**35**
17	2	3	5	**35**	**16**	**22**	**28**
18	1	4	8	**36**	**5**	**7**	**9**

Figure 9 depicts the 36 CDFs of the project completion time when the parameters of the distribution of each task are delayed by one time unit. Note that there is no clear CDF that dominates the other CDFs, suggesting that no particular task stands out as resulting in the longest or shortest project completion time across all percentiles when delayed. The median of the distributions is between 286 and 288 time units. Difficult to discern with the overlap in CDFs, but the CDFs in black represent those tasks belonging to the critical path in Table 3.

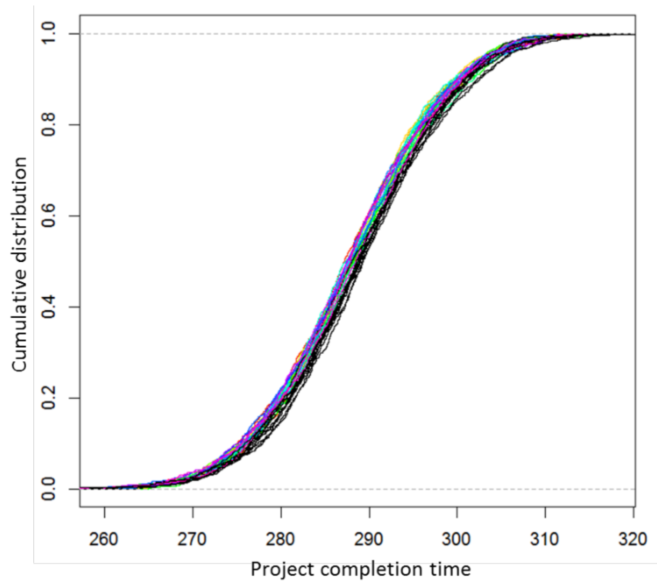
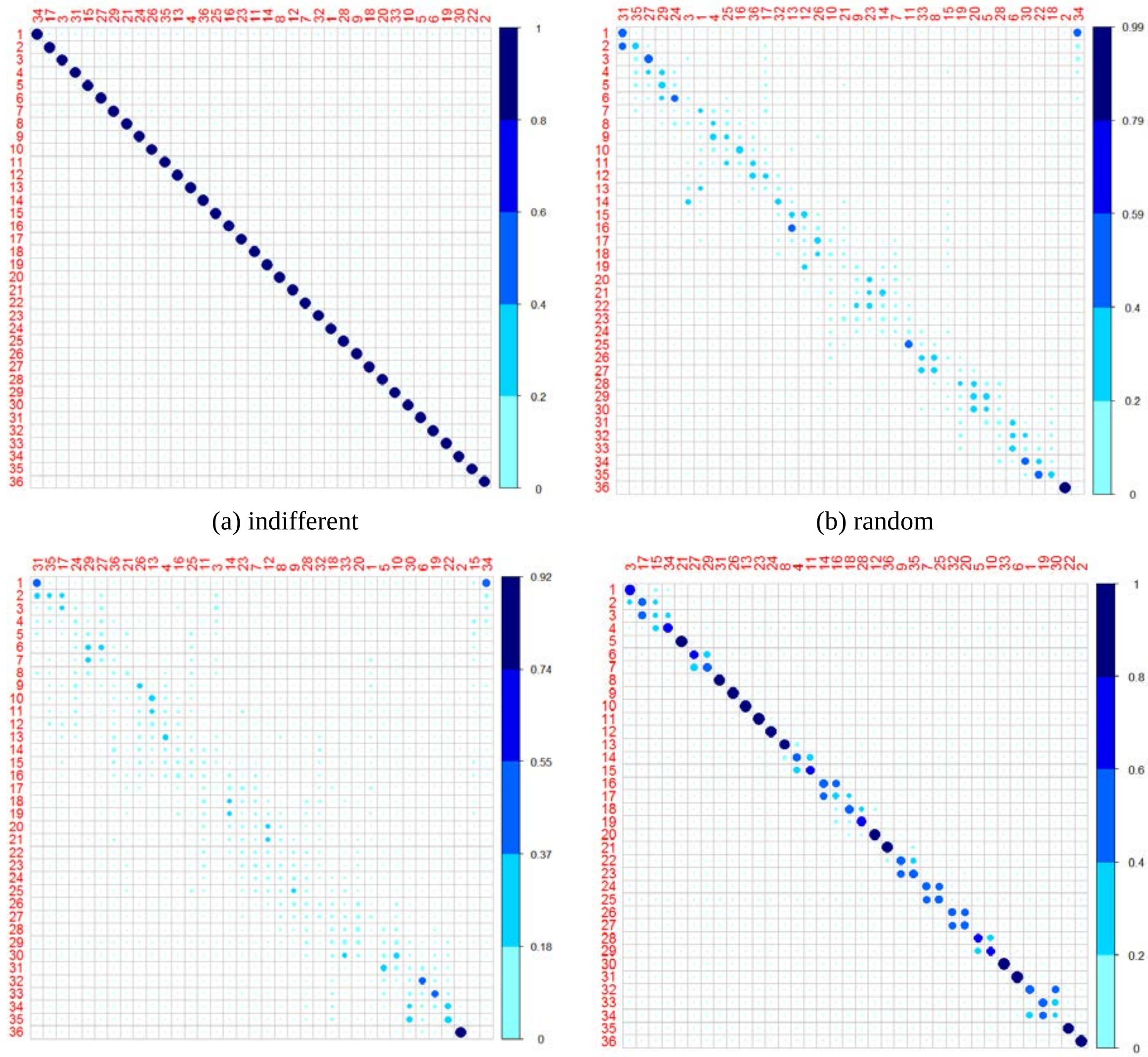


Figure 9. Cumulative distributions of project completion time given a one-at-a-time +1 shift in task completion times for example 1.

Figure 10 provides heatmaps corresponding to the rank of the tasks when the TOPSIS procedure is applied under the four risk preferences. Due to the random generation of decision maker criteria, a single ranking cannot be determined. Instead, an entire distribution of rankings is generated for each simulated project delay and decision maker profile. To visualize the frequency of each ranking, a heat map is generated to understand which tasks are consistently ranked. The rank of tasks is read vertically, and the task number is read horizontally. The relative frequency of the task being ranked at a particular level is given with the size and color of the circle at the intersection. For example, the four most important tasks in the case of equal weights are 34, 17, 3, and 31, and given that there is no uncertainty associated with the weights in this scenario, those tasks are given each of those ranks with probability 1. For another example, in the random weighting scheme, tasks 31 and 34 most often appear as ranked as the most impactful task, and task 2 is always the least impactful. Note that, no matter the risk preference representation being considered, tasks not belonging to the critical path are considered more impactful than those on the critical path. The diversity of tasks ranked in the first positions, for every preference modeled, reveals that the approach, for a shift of +1, produces contradictory results.



(a) indifferent (b) random

(c) central tendency (d) risk averse

Figure 10. Heatmaps corresponding to the rank of tasks given a one-at-a-time +1 shift in task completion times for example 1 for the four decision maker preferences.

One can imagine how the heatmaps in Figure 10 could be used as decision support tools to compare suppliers under uncertain criteria. For example, one could draw conclusions about which suppliers to select under different risk preferences. This application is still ongoing.

6. Conclusions

The study provided a means to evaluate and select suppliers based on their ability to enhance supply chain resilience when a primary supplier is disrupted. As the availability of particular systems is important, availability is chosen as the primary measure of supply chain performance. Resilience is addressed with the combination of (i) improvement in supply chain availability and (ii) the time required for an alternative supplier to become available to the supply chain. Other criteria, including common supply chain characteristics of supplier quality and delivery rate, were also included. Ultimately, a multi-criteria decision analysis technique, TOPSIS, was used to rank the alternatives across the multiple criteria and their importance.

A small (initial) illustrative example helps illustrate how an algorithm for multi-echelon supply chain availability can be used in a supplier evaluation and selection problem that emphasizes supply chain resilience. Future work will expand this initial illustration to a larger supply chain, while performing a sensitivity analysis of criteria weights.

With respect to accounting for uncertainty in the supply selection process, we developed an approach to comparing multiple alternatives (i) described by random variables and (ii) across several risk preference scenarios using TOPSIS. This approach was initially illustrated with a project risk example, and a supply selection example is ongoing.

6.1. Research Output

Results were presented at the 2016 Acquisition Research Symposium, and Barker et al. [2016] was published in the proceedings. A larger scale work is still ongoing, and a manuscript will be submitted in coming months.

A manuscript detailing the stochastic ranking approach applied to project risk has been submitted [Floyd et al. 2016], and a supplier selection illustration is in progress.

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