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An Approach for Modeling Supplier Resilience

Barker, Kash; Ramirez-Marquez, Jose Emmanuel;
Hosseini, Seyedmohsen

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An Approach for Modeling Supplier Resilience

Kash Barker, Associate Professor, University of Oklahoma
Jose E. Ramirez-Marquez, Associate Professor, Stevens Institute of Technology
Seyedmohsen Hosseini, PhD Candidate, School of Industrial and Systems
Engineering, University of Oklahoma

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Panel 15. Connecting Contracting Strategy to Acquisition Outcomes

Thursday, May 5, 2016	
11:15 a.m. – 12:45 p.m.	<p>Chair: Major General Kirk F. Vollmecke, U.S. Army, Program Executive Officer, PEO IEW&S</p> <p><i>Contract Design, Supply Chain Complexity, and Accountability in Federal Contracts</i></p> <p>Adam Eckerd, Assistant Professor, University of Tennessee Amanda Girth, Assistant Professor, The Ohio State University</p> <p><i>An Approach for Modeling Supplier Resilience</i></p> <p>Kash Barker, Associate Professor, University of Oklahoma Jose E. Ramirez-Marquez, Associate Professor, Stevens Institute of Technology Seyedmohsen Hosseini, PhD Candidate, School of Industrial and Systems Engineering, University of Oklahoma</p> <p><i>Antecedents and Consequences of Supplier Performance Evaluation Efficacy</i></p> <p>Timothy Hawkins, Lt Col, USAF (Ret.), Assistant Professor, Western Kentucky University Michael Gravier, Associate Professor, Bryant University</p>



An Approach for Modeling Supplier Resilience

Kash Barker—is an Associate Professor in the School of Industrial and Systems Engineering at the University of Oklahoma. Dr. Barker and his students in the Risk-Based Decision Making Laboratory are primarily interested in (i) modeling the reliability, resilience, and interdependent economic impacts of disruptions to critical infrastructure networks and (ii) enhancing data-driven decision making for large-scale system sustainment. He received his PhD in systems engineering from the University of Virginia, where he worked in the Center for Risk Management of Engineering Systems. [kashbarker@ou.edu]

Jose Emmanuel Ramirez-Marquez—Ramirez-Marquez is an Associate Professor in the School of Systems and Enterprises at the Stevens Institute of Technology and the Director of the School's Engineering Management program. Dr. Ramirez-Marquez's work advances systems management and assessment for optimal development of a system through its life cycle. His other interests include reliability analysis, network resilience, and optimization. He received his PhD in industrial engineering from Rutgers University. [jmarquez@stevens.edu]

Seyedmohsen Hosseini—is a PhD candidate in the School of Industrial and Systems Engineering at the University of Oklahoma. His primary research interests include resilience modeling of supply chains, reliability engineering, and meta-heuristic optimization. [m.hosseini@ou.edu]

Abstract

Supplier selection plays a key role in the context of supply chain management. As recent emphasis has been placed on supply chain resilience, so too should such emphasis be placed on resilient suppliers. In particular, this work evaluates how different suppliers enable the supply chain to withstand the impacts of a disruption and return performance to a desired level in a timely manner. The primary measure of supply chain performance is taken to be availability, or the extent to which the products produced by the supply chain are available for use (measured as a ratio of uptime to total time of the use of the product). Available systems are important in many industries, particularly in the Department of Defense, where weapons systems are required in short notice but undergo regular maintenance activities. In addition to availability, suppliers are also measured according to their recovery rate, quality, and delivery rate. Suppliers are evaluated against these four criteria using a multi-criteria decision analysis technique.

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, 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 on time at the right price. Supplier selection is a multi-criteria decision making problem that involves two major tasks: (i) determine the criteria to be considered and (ii) compare the eligibility of suppliers. Generally speaking, the traditional



criteria associated with supplier selection can be divided into 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, Rosenber, & Barnes, 2009; Liao & Kao, 2011; Arikani, 2013; Lienland, Baumgartner, & Kunbbsen, 2013; Yu & Wong, 2015).

Although research efforts have been dedicated to supplier evaluation and selection, accounting for resilience-based criteria for supplier selection has not been well explored (Hosseini & Barker, 2016). 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 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, Dani, & Burnard, 2011). The impact of the earthquake disaster on the 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 U.S. 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.

In this paper, we explore supply chain availability as a measure of resilience and use this measure in a set of supplier selection criteria. The following section offers some background on several components of the research, including the Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS). The section following that discusses the supplier evaluation and selection criteria used in this work, and the section titled Illustrative Example offers an illustrative example of the methodology. Concluding remarks are provided in the final section.

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.



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., 2015). In particular, this work adopts a graphical paradigm of system behavior before, during, and after a disruption is provided in Figure 1 (Henry & 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 $t_e - t_0$, 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 $t_d - t_e$. The recovery of the system to its *Stable Recovered State*, S_f , occurs during the time interval $t_f - t_d$.

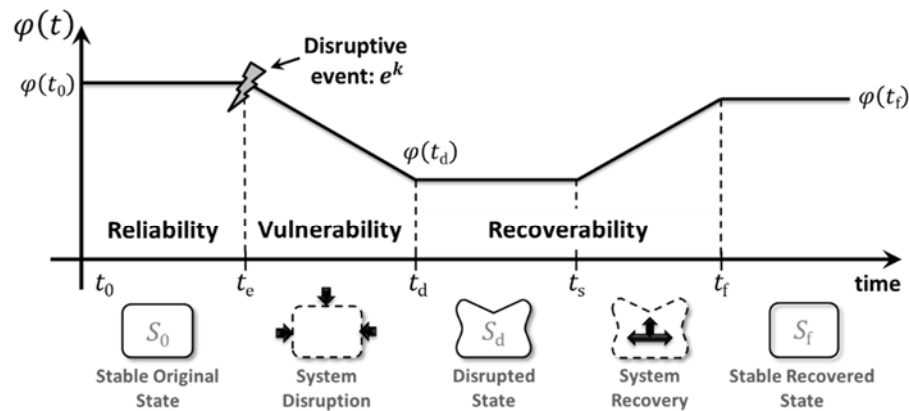


Figure 1. Graphical Depiction of Decreasing System Performance, $\varphi(t)$, Across Several State Transitions Over Time

Supplier Selection Approaches

Various methods have been implemented to deal with supplier selection problems, 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 decision makers to consider multiple aspiration levels. Kilincci and Onal (2011) employed a 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, Benyoucef, and Kumar Tiwari (2015) proposed a fuzzy hybrid multi-criteria decision analysis approach based on combining fuzzy consensus-based possibility measure and fuzzy TOPSIS. Kar (2014) integrated fuzzy AHP and fuzzy goal programming for the supplier selection problem. Lee, Cho, and Kim (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, You, Liu, and

Zhen (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, Hayajneh, and Batieha (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, Hu, Deng, and Mahadevan (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.

TOPSIS

TOPSIS, which will be used in this paper for combining supplier performance along several criteria, 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 i th alternative for the j th criterion. The weight of importance of the j th 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 $j = 1, \dots, n$ Equation 1 represents one such approach to normalizing the value of the criteria (which could be of different magnitudes) for each alternative.

$$n_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^m x_{ij}^2}} \quad (1)$$

Step 2. Calculate the weighted normalized value v_{ij} with Equation 2.

$$v_{ij} = w_j n_{ij} \quad (2)$$

Step 3. Determine the positive ideal solution A^+ and the negative ideal solution A^- with Equations 3 and 4, 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.

Equation 7 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 C^+ and largest from set C^- , is provided in Equation 8.

$$A^+ = \{v_1^+, \dots, v_n^+\} = \left\{ \left(\max_i v_{ij} \mid j \in S_B \right), \left(\min_i v_{ij} \mid j \in S_C \right) \right\} \quad (3)$$

$$A^- = \{v_1^-, \dots, v_n^-\} = \left\{ \left(\min_i v_{ij} \mid j \in S_B \right), \left(\max_i v_{ij} \mid j \in S_C \right) \right\} \quad (4)$$



Step 4. Calculate Euclidean distance between each alternative and the positive and negative ideal solutions with Equations 5 and 6, respectively, for all i .

$$S_i^+ = \sqrt{\sum_{j=1}^n (v_{ij} - v_j^+)^2} \quad (5)$$

$$S_i^- = \sqrt{\sum_{j=1}^n (v_{ij} - v_j^-)^2} \quad (6)$$

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

$$RC_i = \frac{S_i^-}{S_i^+ + S_i^-} \quad (7)$$

Step 6. Rank the alternatives according to RC_i in Equation 7. 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 .

Supplier Selection Criteria

Dickson (1966) introduced 23 supplier selection criteria still found in literature today, including quality, delivery, performance history, and price. Recently, Hosseini and Barker (2016) characterized supplier selection criteria into *primary* (i.e., traditionally used criteria with a history in the literature), *green* (i.e., environmentally-focused criteria recently appearing in the literature), and *resilience* (i.e., dealing with a supplier's ability to withstand and recover from a disruption) categories.

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, Randall, and Ramirez-Marquez, 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).



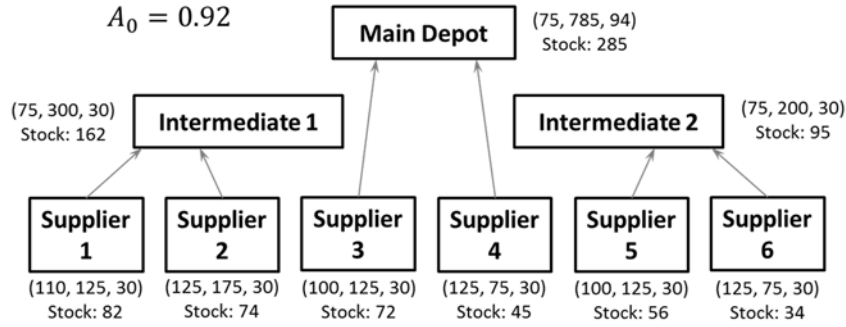


Figure 2. Supply Chain Topology and Characteristics Resulting in an Availability of 0.92

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 Equation 8 (Nowicki et al., 2012).

$$BO(N_i^{le}(t)|s_i^{le}) = \begin{cases} N_i^{le}(t) & \text{if } N_i^{le}(t) > s_i^{le} \\ 0 & \text{otherwise} \end{cases} \quad (8)$$

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 backorders can be calculated with Equation 9, where x is the random variable.

$$E[BO(N_i^{le}(t)|s_i^{le})] = \sum_{x=s_i^{le}+1}^{\infty} (x - s_i^{le}) P[N_i^{le}(t) = x] \quad (9)$$

Finally, Sherbrooke (2004) demonstrated that the availability of a multi-echelon supply chain denoted by A_0 system can be calculated with Equation 10.

$$A_0 = 100 \prod_{l=1}^{L^E} \prod_{i=1}^{I^{lE}} (1 - E[BO(N_i^{le}(t)|s_i^{le})]/n)^n \quad (10)$$

In this study, we would like to identify a backup supplier who can improve the availability of the 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.

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 ability to meet specifications consistently is referred to as *quality*, 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 deliveries 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.

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 Equation 10. More information about how the availability of multi-echelons can be calculated can be found in Sherbrooke (2004).

It is assumed that supplier 1 is disrupted and becomes inoperable, as illustrated in Figure 3. The availability reduces from 0.92 to 0.80.

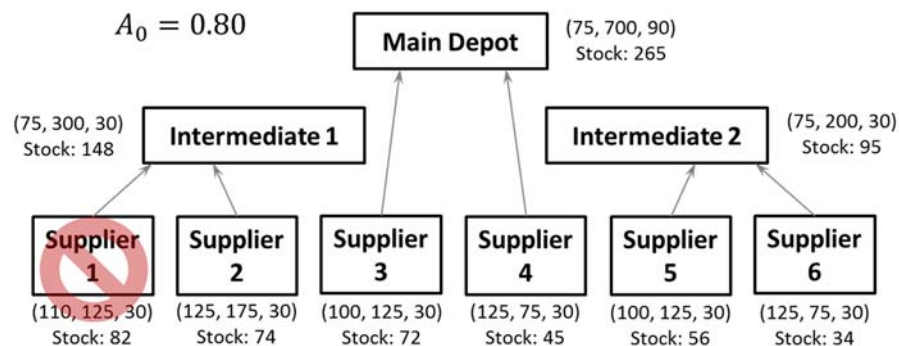


Figure 3. Availability Reduction When Supplier 1 Becomes Inoperable

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 4 provides an illustration of the resilience, or the combination of availability improvement and recovery time, of the three suppliers.

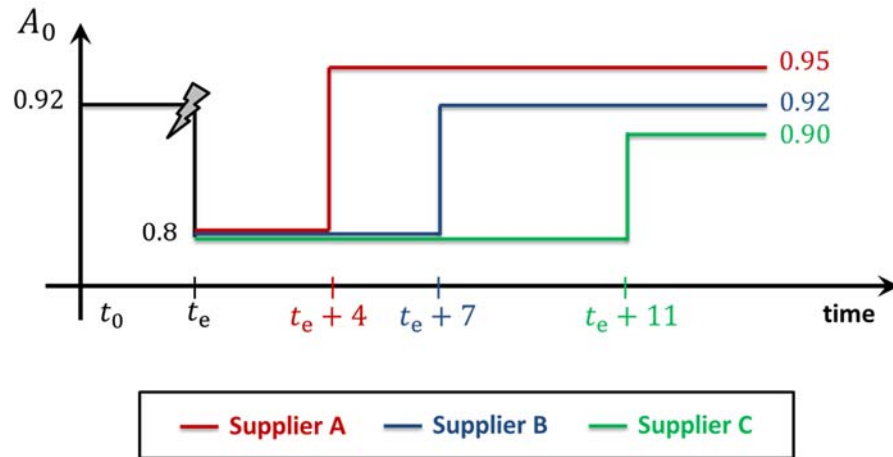


Figure 4. Depiction of the Contributions of the Three Alternative Suppliers to Supply Chain Resilience

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 $w=[0.3,0.3,0.2,0.2]$ 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. As 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 1. 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

Conclusions

The study provides 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.

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