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A MEASURE OF SUPPLY CHAIN COMPLEXITY INCORPORATING VIRTUAL ARCS

Julie Drzymalski

Department of Industrial Engineering and Engineering Management, Western New England University

jdrzymalski@wne.edu (✉)

Abstract

Increased globalization, as well as the ability to have virtual supply chain partners, has had numerous effects on supply chains. While some of these effects are positive, making more resilient supply chains, there are also the negative effects of scale and complexity, making these supply chains more challenging than ever to manage. Having a means to measure the complexity is crucial for today's managers to make more informed decisions. This measure must not only account for the number of arcs, but the amount of information and material carried on it, as well as incorporate the benefit that virtual arcs add to the network by increasing efficiency and reducing information, product and financial transfer costs and time. This research utilizes newer models in network clustering and complexity theory to make them applicable to supply chains and creates a new, practical approach to measuring supply chain complexity which can be easily implemented by practitioners.

Keywords: Supply chain, complexity, clustering, virtual networks

1. Introduction

The effects of globalization on organizations are numerous, often resulting in very large and complex supply chains. Companies opt for globalization in order to be more competitive in areas such as cost, life-cycle, lead time and quality. Demanding consumers compel corporations to provide a wider range of products with increased customization which in turn force companies to expand their supply base, leading to very complex networks. However, complexity of a network is directly correlated to supply chain performance (Perona and Miragliotta 2004, Caridi et al. 2010), therefore measuring this complexity is a necessity for supply chain managers to make informed decisions. As an example, consider a supply chain with all nodes in a particular stage linked to all upstream and downstream nodes. While probably a resilient supply chain, it also makes a very complex supply chain, highly prone to disruption, particularly when no echelons contain redundant suppliers. It is crucial then to be able to calculate supply chain complexity and include it as a performance measure in the network design process.

Measuring network complexity has begun to take the interest of researchers recently in order to better manage the activities within the supply chain. In dealing with supply chains, different viewpoints are taken as to what comprises the complexity. Number of supplier relationships and their inter-relationships (Choi et al. 2001, Choi and Krause 2006), supplier reliability (Vollman et al. 2005), and level of globalization (Nellnore et al. 2001) are oft-cited factors to complexity. To measure supply chain complexity, we must include both a measure of the amount of product, information and finances flowing in the supply chain as well as a measure of the denseness of the network. However, supply chain complexity can be reduced when information or material is transmitted electronically (Rogerson and Fidler 1994, Nagurney et al. 2005). E-commerce can create value for an organization by lowering transaction costs, eliminating "storefront" costs and increasing visibility. Additionally, a company that delivers electronic products such as movies and books saves on distribution and shipping costs. Considering that the volume of electronic commerce in the United States alone has risen by approximately 15% every year since 2009 (Commerce 2015), an additional factor accounting for virtual arcs and the value they add to the resiliency of the network should be included in the complexity calculation as well.

Complexity can be measured in many different ways and spans many fields such as social science, biology and engineering. In network analysis there has been significant research into measuring the basic topological features. Parameters such as number of connected components, degree distributions, connectivity and shortest paths are often cited as measures of the network topography (Doncheva et al. 2012), however, most of these ignore the weights that exist on the arcs such as in a supply chain. This research combines the field of supply chain management and complexity to expand existing complexity measures to be applicable for supply chains which are virtual, "brick and mortar" or a hybrid of both.

The contribution of this research is two-fold: first, measures of strength and clustering of the supply chain are developed, which have the ability to accommodate virtual arcs and their lessening effect of risk on the supply chain. Second, utilizing these measures, a formulation for supply chain complexity is developed, which can be used as a comparative guide across various supply chain configurations and weights since the complexity value lies between 0 and 100%. Section 2 first details the literature on complexity, followed by network clustering measures and a review of virtual supply chains. The methodology is developed in Section 3 and a simulation model and conclusions are in Sections 4 and 5, respectively.

2. Background

The field of complexity spans many distinct areas such as computer science, sociology, biology, mathematics and physics and researchers have developed many metrics for measuring the complexity and clustering of a network. This research combines both fields, thus the background will describe measures developed for complexity of general networks, supply chain networks and specifically entropic complexity measures. A review of network clustering and virtual supply chains are given in Sections 2.2 and 2.3 respectively.

2.1 Complexity

2.1.1 General Network Complexity Measures

Pascoe (1966) defined the coefficient of network complexity (CNC) as the ratio of arcs to nodes and Kaimann (1974) refined this as the ratio of the number of activities squared, divided by the prior work items squared, divided by the number of work items for an activity on arc network (AOA). Similarly, Bonchev and Buck (2005) discuss and compare several traditional methods used to analyze complexity of networks. They compare global, average and normalized edge complexity, second order subgraph count and overall connectivity. The cyclomatic number, developed by McCabe (1976) was generalized by Hall and Preiser (1984) to account for allocation of resources which is suitable to compare one network to another. The authors further modified this into a combined measure to include module and network complexity. Measures proposed by Henry and Kafur look at the coupling between modules (Henry and Kafura 1981) while Troy and Zweben look at program structure as a measure of complexity (Troy and Zweben 1981).

More recently, Meepetchedee and Shah define complexity as the ratio of the number of network edges to the number of minimum spanning tree edges of the smallest network (Meepetchdee and Shah 2007). The model for the h-index used by authors is used as a basis for Bailey and Grossman's network complexity index (Bailey and Grossman 2013). DeReyck and Herroelen (1996) discuss reduction of the network as a measure of complexity. The authors define the complexity index as the minimum number of node reductions sufficient to reduce a two terminal acyclic network to a single edge. Complexity of business process models, as they are akin to software models are developed by Laue and Gruhn (2006). Keating's measure of complexity (Keating 2000) is used by Stuikys and Damasevicius (2009) to propose three new measures for measuring domain model complexity when modeled with feature diagrams.

Most of the above measures can yield different interpretations of the network complexity as it is related to its topology. Some exceptions are Hall and Preiser (1984) who accounted for complexity of each node and edge and the simplistic standard measures of average vertex distance and average degree of vertex to vertex separation. However a supply chain is a directed, weighted graph with varying weights on each arc due to distances, costs, leadtime and the like. To account for this, Barrat et al. (2004) developed a measure of complexity which accounts for the capacity and intensity of the arcs. In the measure, vertex strength is calculated as the weighted sum of the arcs entering and exiting the vertex. This is furthered by finding the clustering coefficient of weighted nodes and arcs, providing a measure of congestion at the nodes.

2.1.2 Supply Chain Complexity

Supply chains fall in the class of scale free networks (Sun and Wu 2005) and typically, their properties are not normally distributed and their degree distribution is characterized by power distributions (Bailey and Grossman 2013, Meepetchdee and Shah 2007), making the task challenging. The literature on supply chain complexity is sparse, however, more recently, researchers have been analyzing a supply chain network as a complex system (Choi et al. 2001, Mabert and Venkatarmanan 2009, Pathak et al. 2007). The issue with most of these taxonomies is that they focus on one firm as the central point, yielding a greedy analysis of the system (Harland et al. 2001). Others look at one factor as the key to understanding complexity of the network. For example, Grandori and Soda (1995) look at human resources to leverage their relative power in the SC. Looking at a supply chain triad, Madhavan et al. (2004) researched the dimensionality of the network concluding that complexity increases with an increasing number of triads. Choi and Krause (2006) look at complexity of the supply side as a function of three factors: the number of suppliers, their differentiation and their level of interrelationship. Using this theory, Skilton and Robinson (2009) correlate the level of complexity to the traceability of adverse events in the SC.

2.1.3 Entropic Measures

Few researchers have been looking at supply chain complexity through the eyes of network complexity. Entropy measures have been used to study manufacturing complexity, many utilizing Shannon's entropy measure of the level of information in an unclear signal (Shannon 1948). For example, Deshmukh et al. (1992, 1998) and Frizelle and Woodcock used Shannon's entropy method to measure structural (static) and operational (dynamic) complexity (Frizelle and Woodcock 1995). Isik (2010) amended their work by added a complexity level for each state probability. Manufacturing complexity has been studied by a few researchers. Calinescu et al. (1998) combined Frizelle and Woodcock's work with Meyer and Foley Curley (1995) to calculate production system complexity, while Shih and Efstathiou (2002) utilized an algorithmic approach to investigate complexity of various manufacturing networks.

Other authors have focused their entropic methods to analyze and measure the level of uncertainty within the flows of the network (Karp and Ronen 1992, Sivadasan and Efstathiou 2002), although their networks are limited to a newsvendor type situation. Perhaps the paper most closely aligned with this research and one of the only papers to consider SC network complexity utilizing entropic measures was Allesina et al. (2010). The authors apply eight different measures of entropy in a supply network and compare the results. This initial work proposes that, while each of these measures are necessary due to the different point of view each takes, further work is necessary to compile this into a practically applied measure.

2.2 Network Clustering Measures

The standard measures of clustering are either local (restricted to a particular node) or global (over the entire network). One common local technique is to use the ratio of actual arcs that exist from a node to the number of possible arcs that could exist (Wasserman and Faust 1994). One of the issues with this method is that directionality of the arcs is ignored. Furthermore, Soffer and Vazquez proved that a node with a large degree vertex that is connected to a node with a much smaller degree vertex will always yield small local clustering (Soffer and Vazques 2005). To overcome this, the authors developed a three vertex correlation which effectively removed the degree correlation from the local measure. Others have overcome the issue by setting a threshold value for weighted graphs, making it a binary graph: arcs which exceeded the threshold were given a weight of one and the remainder had zero weight. More recently, Barrat et al. (2004) and Zhang and Horvath (2005) extended the local measures by including a factor for weighted graphs.

Global measures are based on the notion of transitivity which is a measure of balanced or closed triads, namely the proportion of triads that are closed in directed graphs. There are two common global measures: one is the ratio of the average number of arcs that exist to the average number of arcs that could possible exist. While the other uses the local measure and finds the average of nodes with degree larger than one (Opsahi and Panzarasa 2009). In order to make it usable for weighted graphs, some authors have again used the threshold value technique. (Wasserman and Faust 1994). Opsahi and Panzarasa (2009) utilize the geometric mean of the weights and compares the value of closed triplets to the total possible value of triplets. Onnela et al. (2005), Zhang and Horvath (2005), and Holme et al. (2007) also developed various clustering measures for weighted networks. Soffer and Vazquez (2005) compare each of these methods and discuss the shortcomings of each.

2.3 Virtual Supply Chains

It has been shown that the use of electronic information can greatly reduce the complexity of supply chains (Rogerson and Fidler 1994, Nagurney et al. 2005). While the literature on the effect of virtual or electronic supply chains is vast, to the author's knowledge, there is no literature currently quantifying the effect on complexity with the inclusion of one or more virtual links. Not only does a virtual link reduce the complexity, those organizations that rely on electronic transport of information, money and/or product also demonstrate more efficient and effective flows (Chandrashekar and Schary 1999). Thus, when considering SC complexity, the weight of those virtual arcs should not be given as much consideration due to their lack of volatility. Here, an additional factor accounting for virtual arcs and the value they add to the resiliency of the network will be included in the complexity calculation as well.

This research combines a complexity measure incorporating the size or strength of the network and a measure of clustering along with a means of accounting for virtual arcs in order to determine overall complexity. Here, the measure of complexity (termed "strength" in this paper) utilized in Section 3.1 is similar to total system throughput seen in Allesina et al. (2010), however, includes weighted nodes as well as arcs like that proposed by Barrat (2004), which is used in conjunction with a modified measure of clustering. Typical measures of clustering utilize the ratio of the number of closed triads in the network to the total possible number of triads in the network, however, as with most supply chain studies, we assume that there is no "within echelon" link, meaning that the flow either goes up or downstream and not vertically and thus, there are no triads. Therefore, the standard measures of clustering must be modified to accommodate this, shown in Section 3.2. Finally, since e-commerce plays an ever-increasing role in every country's GDP, some means of accounting for these must be included. The combination of these two measures gives a unique and more robust measure of supply chain complexity, accounting for not only the weight of the system but the density as well, while incorporating virtual arcs. It is easily implemented in practice.

3. Methodology

A supply chain has three principal flows: material, information and financial. Each of the three principal flows in the supply chain (material, information and financial) has various parameters which define them. For example, product flow can be defined by the lead time, distance and logistics cost. Additionally, in today's global, electronic marketplace, these flows can be either virtual or physical and all of the flows within one supply chain need not be unique with respect to that characteristic. For example, ordering an item of clothing online will dictate a physical material flow (for the item to be shipped to you) and a virtual information and financial flow.

The following are defined:

K = set of supply chain flow types,
$K = \{1, \cdots, k\}$,

L = set of parameters for each flow type,
$L = \{1, \cdots, l\}$,

N = set of nodes in the supply chain,
$N = \{1, \cdots, n\}$,

W_{ijkl} = weight of parameter l for arc i to j in flow type k,
$i, j \in N, k \in K, l \in L,$

W_{ijkl} = 1 if arc i to j exists for parameter l in flow type k, else, 0,

Φ_{SC} = strength of supply chain.

Two measures will be developed and later, combined. The first, supply chain strength, will account for the weight and virtuality of the arcs, while the second will take the density of the network into account.

3.1 Supply chain strength

Each individual flow and the corresponding data (weights) will be measured utilizing the complexity measure developed by Barrat et al. (2004) , as it is one of the few network measures that incorporates weighted arcs and nodes.

Let,

S_{ilk} = strength of node i for parameter l in flow type k,

S_{ik} = strength of parameter l in flow type k.

Using the measure for strength defined in Barrat et al. (2004) and the above-defined variables, the strength of node i for each parameter l within each flow k and is given by:

$$S_{ilk} = \sum_{j=1}^{n} a_{ijlk} w_{ijlk}. \tag{1}$$

It is important to note here, that since one of the aspects of this research is virtual arcs, the value of w_{ijlk} will be zero when the particular arc is a virtual arc ($0 \le w_{ijlk} \le \infty$). Unity-based normalization is used here for convenience (distinguished here as $\tilde{S}_{ilk}$) and calculated as shown in Equation 2.

$$\tilde{S}_{ilk} = \frac{S_{ilk} - \min(S_{lk})}{\max(S_{lk}) - \min(S_{lk})}, \forall l \in L, k \in K. \tag{2}$$

Supply chain strength is found by the mean of each parameter in each of the three network flows shown in Equation 2. Due to the data normalization, this value for overall supply chain strength, shown in Equation 3, can be used as a relative measure since it lies between zero and one.

$$\Phi_{sc} = \frac{\sum_L \sum_K \sum_N \tilde{S}_{ilk}}{NLK}. \tag{3}$$

The term strength used here is actually paradoxical in the traditional sense. As discussed previously, some arcs can be virtual, which will reduce the true weight of the arc on the supply chain since, for example, a virtual transfer of funds or product will offer much less potential for complications in the supply chain such as delayed or late payments, lost or incorrect shipments. Thus two networks with identical weights but with different degrees of virtuality will give different values for strength; the one with a higher percentage of virtual arcs will provide a lower strength value. The greater the value for the strength in each of the flows the heavier the flow is, meaning that the strength is a function of the quantity of arcs and their weights, and the number of virtual arcs. If supply chain strength is defined as above, then ideally, a less weighted, less congested network would simplify the supply chain and yield a lower strength. However, a less congested network also means less backup suppliers which would make the supply chain riskier and prone to disruptions. Therefore, while a higher value of strength is traditionally thought of as something positive, here, it will yield a value of higher supply chain complexity, which may not be desired. Hence, it is valid for the purposes of measuring complexity. The strength measure will be combined with the clustering measure, discussed next.

3.2 Supply Chain Clustering

The typical definition of clustering coefficient is given as the ratio of the number of closed triads in the network to the total possible number of triads in the network. Opsahl and Panzarasa (Clustering in weighted networks 2009) extended this to a weighted clustering coefficient by finding the ratio of the geometric mean of the closed triads to the geometric mean of all possible triads. We have accounted for the weights and virtuality in the strength measure, thus accounting for them here will only exaggerate them. Also, as discussed previously, a supply chain will typically not have any triplets. The supply chain clustering coefficient will be defined simply as the ratio of the number of total upstream and downstream suppliers a node is connected with to the total number of possible up and downstream suppliers, regardless of whether they are physical or virtual arcs. Shown in Equation 4, the complexity for node i is the ratio of the number of edges connected to the vertices in the neighborhood of node i divided by the total number of vertices in the neighborhood of node i.

$$\rho_i = \frac{\left|\left\{e_{ij} : v_j \in N_i, e_{ij} \in E\right\}\right|}{k_i}, \qquad (4)$$

where,

e_{ij} = 1 if the edge from i to j exists, else 0,
N_i = neighborhood of node i,
E = set of edges,
V_j = vertex j,
k_i = number of vertices in the neighborhood of i,
ρ_{SC} = supply chain clustering.

Supply chain clustering is the average clustering of the nodes in the supply chain as shown in Equation 5.

$$\rho_{sc} = \frac{\sum_{i=1}^{N} \rho_i}{N}. \qquad (5)$$

3.3 Supply Chain Complexity

Here we will combine the measures for supply chain strength and clustering to be used as a final measure for supply chain complexity. The chosen model is a power model since networks are characterized by power distributions (Meepetchdee and Shah 2007) and supply chain clustering is fractional ($0 \le \rho \le 1$).

$$\text{Supply Chain Complexity} = \Phi_{sc}^{(1/\rho_{sc})}. \quad (6)$$

Using this model, a complete network – one in which each supply chain member is connected to all of its up and downstream partners – will have a complexity value equal to supply chain strength and since both strength and the clustering inverse lie between zero and one, an increase in clustering will yield an increased complexity, as desired. As discussed in Section 3.1, a larger value for supply chain strength indicates both larger arc weights and more physical (non-virtual) nodes. Since both of these are indicators of a more complex supply chain, the chosen representation is appropriate.

4. Simulation

In order to demonstrate the complexity measure, a simulation model was performed. The purpose is to simulate various possible supply chain scenarios, with varying percentages of weighted arcs and random weights associated with each arc and compare the supply chain complexity due to the clustering effect (% of arcs in the system).

4.1 Simulation Model

The supply chain shown in Figure 1 was used for simulation. So that there always existed at least one path from echelons 0 to 3, the arcs shown as solid were considered fixed and the remaining arcs shown dashed were randomly generated with each simulation, however it was assumed that if a node (in echelons 1 and 2) had at least one entering arc, it also had at least one exiting arc.

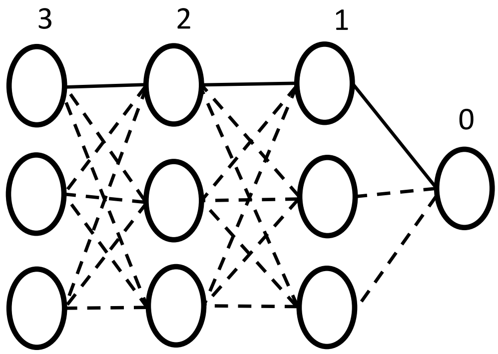

Figure 1 Supply chain simulation model

The set of parameters, l, for each of the k flows (material, information and financial) is defined as virtuality, distance, lead time and cost. In the material flow, distance represents the actual distance to ship a physical product, lead time is time required to ship the product and the cost is that borne by the supplier. In the information flow, distance will be the actual distance the information data needs to travel, lead time is time required to gather the information being sent, and cost is the associated cost with gathering and sending data. In the financial flow, distance is the actual distance the payment must travel, lead time is the average time the supplier is paid in and cost is the payment sum. One of the objectives of this research is to determine the effect of a fully or partially virtual supply chain. A virtual arc is considered for a particular flow if information was delivered electronically, payment was made electronically or product is delivered electronically.

The following sets are defined:

K = {material, information, financial},

L = {distance, lead time, cost},

$N = \{1,\cdots,10\}$.

The random network is generated as described above, considering the one path show in a solid line in Figure 1, and the other arcs generated by a binary random variable (1=existence of arc, 0=non-existent arc), with the assumption that if a vertex in echelon 2 had an entering arc from echelon 1, it also had at least one exiting arc. After the random network was generated, each arc was assigned a binary random variable to designate its virtuality. The weights assigned to each arc are shown in Table 1.

Table 1 Weights used for simulation

Weight Variable	Description	Simulation Value
W_{ijkl}	Weight of parameter l for arc i to j in flow type k, $\forall i,j \in N, i \neq j, k \in K, l \in L$	
	Virtual arcs	$W_{jkl} = 0$
	Non-virtual arcs	$W_{ijkl} \sim U[1,10]$

The total number of possible arcs in the system is 21, therefore the clustering effect, ρ_{SC} is the number of arcs generated for that simulation divided by 21 and the percent of virtual arcs is found in a similar manner. For comparison purposes, a purely physical supply chain (one with no virtual arcs) was also simulated with the same parameters and distributions. Both of the models were simulated 10,000 times each and results are discussed below.

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4.2 Simulation Results

The data is normalized as outlined in Section 3.1 and 3.2 to generate supply chain strengths and complexities for the purely physical and partially virtual networks. Figure II shows the change in strength as more virtual arcs are added to the network. As mentioned earlier, a higher value of strength, is not necessarily desirable, since it increases complexity. As expected from Equations 2 and 6, the general trend is that the more virtual arcs that are added to the network, supply chain strength will decrease. However, it can also be seen that for virtual networks, strength is lower, regardless of how clustered the network can be. It is worth noting that while a purely physical network will always yield 100% of expected strength, even a small percentage of virtual arcs (shown as little as 25% virtual in Figure 2) can reduce this strength by about 15%.

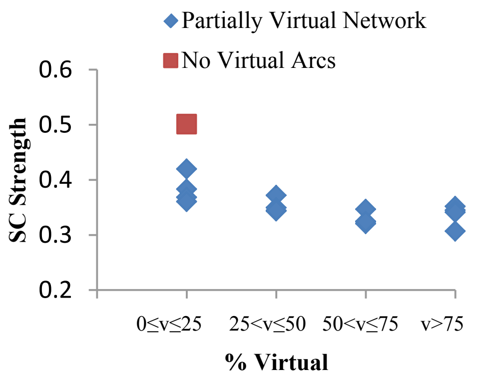

Figure 2 Effect of virtual arcs on SC strength

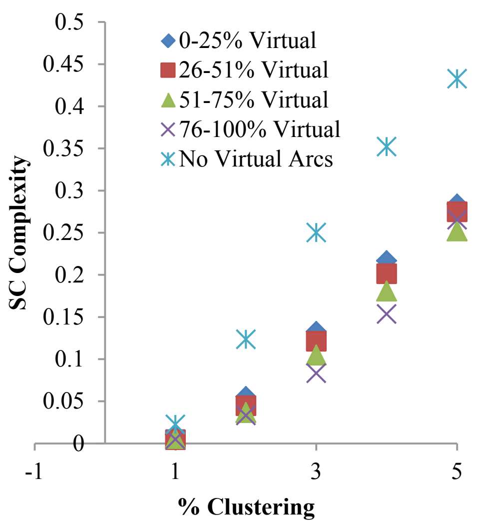

Figure 3 Complexity vs clustering for various configurations of virtuality

Complexity is the focus of this research. Figure 3 shows the calculated complexity value for both the physical and partially virtual networks, respectively. It becomes clear that supply chain complexity increases rapidly with the number of arcs (% of clustering) in the network and that the use of virtual arcs can decrease this significantly. For a supply chain with a clustering percentage of under approximately 40%, the percentage of virtual arcs does not play as large of a role in reducing the clustering factor as much as when the supply chain is more clustered. For large values of clustering (over 80%) however, the addition of even a small number of virtual arcs can reduce the complexity by approximately 30%.

5. Conclusions

Supply chain complexity is an issue that is becoming more prevalent and corporations need to pay attention to this factor in order to maintain a competitive edge. The first step is to have a standard methodology to measure the network. This research presented a comprehensive formulation combining supply chain strength and supply chain clustering to obtain a value for supply chain complexity. The simplicity of the formulation makes it easily adaptable in practice and should be utilized when designing SC networks. Supply chain strength factors in the amount of information/cost/distances involved (arc weights) and the presence of virtual arcs which will reduce overall complexity. The supply chain clustering incorporates the denseness or connectivity of the network. Like most network complexity models, these are combined as a power function for a final supply chain complexity value.

It was shown that strength and complexity generally increase as the connectedness or clustering increases. They both, however, are reduced significantly with an increasing number of virtual links. It is understood that while a virtual supply chain can function more efficiently and accurately, it is also prone to higher risk, thus much literature focuses on risk mitigation and resiliency techniques (Harland, et al. 2003, Chandrashekar and Schary 1999, Kleindorfer and Saad 2005). When designing a SC network, it would be beneficial for supply chain managers to utilize a complexity methodology such as this to find a point at which complexity will be reduced enough but that the desired level of resiliency is maintained. Future work will incorporate risk level of a SC entity into the relative value of a virtual arc. This can be utilized as a methodology to design for optimal complexity based upon a desired risk level.

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Julie Drzymalski is an associate professor and Chair of Industrial Engineering and Engineering Management at Western New England University. She received her Ph.D. in industrial engineering from Lehigh University in 2008. Her research interests focus on supply chain optimization, risk analysis and management and service systems. She is a member of IIE, INFORMS, ASEM and ASEE.