Complex network theory-based approach for designing resilient supply chain networks

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Abstract: Globalisation within supply chains opens many doors for new opportunities but can also result in highly complex, unstable and fragile supply chains. Due to importance of complex network theories in supply chain, the authors examine the advances of complex network theories to understand the properties of these networks in underlying efficient supply chains. In this paper, the resilience metrics for supply chain are developed based on complex network theory. Agent-based simulation approach is used to show the applicability of various complex network models to design the resilient supply chain networks. Simulation results shows that supply chain network can be designed based on complex network theory especially as a scale-free network. It was also concluded that scale-free models have some limitations and cannot accurately represent an efficient and resilient supply chain. Therefore, it is suggested that a scale-free model should be developed that can represent more robust and resilient supply chain networks.

Keywords: resilient supply chain; agent-based simulation; complex-network theory; disruption.

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1 Introduction

In a world of turbulent and uncertain markets, one of the significant and major issues for many companies is supply chain vulnerability. Supply chain risk is mainly characterised by supply chain inefficiencies and inadequate infrastructure. To manage, control and mitigate that risk there is a need for creating more resilient and robust supply chains (Christopher and Peck, 2004). A supply chain risk is mainly characterised by supply chain inefficiencies and inadequate infrastructure (Tang and Lau, 2013). The new strategies must be adapted by supply chains in order to respond more efficiently and rapidly towards the respond to unforeseen changes, complexities and unpredictable disruptions. These disruptions may arise as a result of unexpected man-made or natural disasters such as deliberate sabotage, terrorist attacks, earthquakes, or floods (Carvalho et al., 2012b; Sawik, 2013). The tragic events of 9/11 highlighted some of the risks associated with the dependence on supply chains to move products and information continuously (Glickman and White, 2006) making the need for greater resilience (Carvalho et al., 2012a). The recent literature mainly covering supply chain risk management emphases a lot of attention towards making the more robust and resilient supply networks (e.g., Glickman and White, 2006; Sawik, 2013; Tomlin, 2006; Sheffi, 2006) and the reason may be the increasing number of disruptions.

Modern supply chains have become much more complex consisting of a wide and complex network of interconnected units, including not only suppliers, manufacturers, distributors, retailers and customers but it also includes supplier's suppliers, customer's customers, etc. Because of this increased complexity, many authors have suggested that they are better described as supply networks (Surana et al., 2005). Furthermore, the notion of a complex network has been put forward to describe the design and analysis phase of supply chain (Choi et al., 2001; Pathak et al., 2007). The supply chain is a complex network in which there are huge number of interdependencies and interrelation among different units, resources and processes characterised by a structure spanning several scales. It is highly nonlinear, shows complex multi-scale behaviour and self-organises and evolves through a complex interplay of its structure and function. Therefore, it is very difficult to control and manage the supply chain network with the simple assumptions of linearised set of models (Surana et al., 2005), so new approaches are required to deal with this complex supply network issues (Manzouri and Rahman, 2013). This old 'linear structure' concept has already been found to have changed to 'complex systems' in the context of logistics (Wycisk et al., 2008) making this modern concept of supply chain network is much more complex than the traditional one.

This paper is written to analyse the supply chain network resilience on the basis of complex network topologies. The authors examine the advances of complex network theories to understand the properties of these networks in underlying efficient supply chain. To design resilient supply chain network, the properties of complex network are synchronised with real-world complex supply chain network. In this paper, the resilience metrics for supply chain are developed based on complex network theory. Various important complex network models such as random graphs, Watts Strogatz model, and scale-free (SF) models are compared using agent-based simulation based on developed resilience metrics.

This paper is structured as follows. The first part introduces the reader to complex supply network properties. Then complex network theories are analysed based on resilient supply chain system. The last part of paper compare properties of complex network models using agent-based simulation approach with resilient supply chain network to propose the applicability of complex network models for designing a resilient supply chain.

2 Literature review

The term 'resilience' was first used in the field of ecology by Holling in 1970s. In his work he defined resilience as, "a measure of the persistence of systems and of their ability to absorb change and disturbance and still maintain the same relationships between populations or state variables" (Holling, 1973). Other authors have defined resilience in different ways. Walker and Salt (2006) defined resilience as "the ability of a system to absorb disturbances and still retain its basic function and structure". Resilience in the field of supply chain was first discussed by Christopher and Peck (2004), who defined resilience as, "the ability of a system to return to its original (or desired) state after being disturbed".

In particular, resilience in the context of supply chains has been used as a concept to understand the responses to disaster relief efforts and major supply chain disruptions (Boin et al., 2010; Lodree and Taskin, 2007; Ratick et al., 2008; Spiegler et al., 2012; Tomlin, 2006). Resiliency in supply chains is considered as a way to reduce the severity and likelihood of supply chain disruptions (Mari and Lee, 2012). However, the research to date has been limited to qualitative work with few papers providing a quantitative framework for assessing supply chain resilience (Mari and Lee, 2012).

Therefore, it is necessary to move from theoretical point of view to practical point of view by developing mathematical models to handle disruptions in the supply chain. With the increased complexity associated with the production and delivery of goods or services from the raw materials to the end consumer markets, the alliance of firms has already gone beyond the traditional range of supply chain which gives birth to supply network. Supply network is a set of interrelated supply chains with a large number of suppliers, distributors, retailers, customers and so on. Despite the implication of networks for modelling complex adaptive systems, the literature has few examples of the application of the latest developments in network theory specifically to supply chains. Previous efforts have, in the main, adopted a relational exchange view of a network (Mohammad et al., 2006) or retained an oversimplified dyadic/linear view (Hearnshaw and Wilson, 2013).

Furthermore, the instability in today's business organisations and changing market environments need supply networks to be highly agile, dynamic, re-configurable, adaptive and scalable, in order to efficiently respond to satisfy the demands. Many researchers investigated supply networks by various static approaches such as control theory, programming method, queuing theory. For example, Liu et al. (2005) used two layered optimisation-based control approach to study the multi-product, multi-echelon supply chain network with independent production lines. Holme and Kim (2002) investigated a supply network in the reconfigured distribution system, where resource inputs are constrained to achieve performance goals. Amaral et al. (2000) used optimisation method to explore outbound supply chain network design with mode selection, lead-time and capacitated vehicle distribution centre. Kerbache and Smith (2004) developed an analytical methodology coupled with nonlinear optimisation to design supply chain topologies and evaluate various performance measures, based on queuing networks. They showed that their approach is very helpful for evaluating the performance of the network topologies and also useful for analysing the congestion problem. Tabrizi et al. (2013) proposed multi-product, multi-source, and multi-capacity network design problem in a global state using robust optimisation technique.

Although these simple linear structure models provide some useful suggestions for managers, they cannot reflect the highly dynamic, nonlinear, agile and adaptive characteristics. Managing the supply chain functions become more difficult due to the complexity of supply chain and assumption of simple linear structure models fails to achieve desired objectives (Cheng, 2013).

Different from these static views, many researchers have investigated the dynamically evolutionary characteristics of supply network by other methods such as complex adaptive theory, system dynamics, and agent-based simulation (Huang et al., 2007). Bhattacharya et al. (2012) argued that in order to deal with nonlinearisation and randomness, supply chain networks should be design with the concept of statistical physics and quantum physics. The following section provides insights into important complex network topologies which further helps to understand the relationship of these complex network and supply chain network properties.

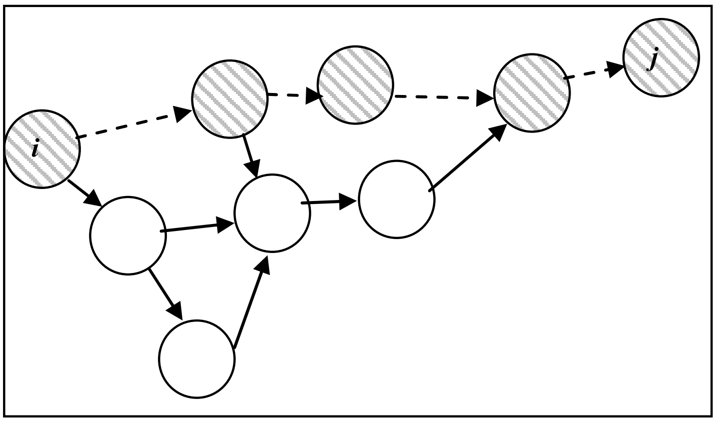
3 Complex network theory and resilient supply chain properties

Previous empirical research into other real-world networks such as social (Newman, 2001), business (Souma et al., 2003), ecological (Sole and Montoya, 2001), biological (Podani et al., 2001), neurological (Bullmore and Sporns, 2009) and communication systems (Albert et al., 1999) highlight a number of key, seemingly universal, network properties derived from self-organising processes. These properties (Barabasi, 2009; Ramasco et al., 2004) evident in efficient real-world networks are a *short characteristic path length*, a *high clustering coefficient* and the presence of a *power law connectivity distribution*. There is sufficient argument and empirical evidence to show that these same three properties are also present in efficient supply chain systems (Hearnshaw and Wilson, 2013).

Traditionally, the concept of complex networks has been considered as a part of graph theory. While graph theory initially focused on regular graphs, since 1950s large scale networks with no apparent design principles have been described as random graphs, proposed as the simplest and most straightforward realisation of a complex network. Random graphs were first studied by the Hungarian mathematicians Paul Erdos and Alfred Renyi. Since its introduction, this model has played a vital role in guiding and explaining the basic nature of complex networks. It works well for decades but because of the increasing interest towards the complex systems many researchers has been motivated to reconsider this modelling paradigm. In the last few years we have seen many new advancements and developments taking place in this area and many new measures and concepts has been investigated and proposed in depth, prompted by these converging improvements and circumstances (Albert and Barabasi, 2002). Since the last decade various topological metrics of complex networks are introduced; however, three concepts occupy a prominent place in contemporary thinking about complex networks, i.e., small world, degree distribution and clustering coefficient. These are briefly explained next.

A *small-world* (*SW*) *network* concept refers to collaborative networks in which the mean shortest-path distance between nodes increases sufficiently slowly as a function of the number of nodes in the network. The small world property are also referred to as short characteristics path length. The term 'SW network' is often frequently used interchangeably with Watts-Strogatz toy network or W-S model. The term is often applied to a single network in such a family. As a property of network, characteristic path length of supply chain network shows the average number of firms that must be crossed between any two firms selected at random (Hearnshaw and Wilson, 2013). For example, in material flow from supplier *i* to customer *j* the shortest path consist of five nodes (firms) as shown in Figure 1.

Figure 1 Determination of shortest path length in material flow



The *degree distribution* contains a very small portion of the total information regarding a network. But this small portion gives significant hints into the structure of a network. For example, if we examine the simplest type of networks, we can easily find that the majority of the nodes in a network contain similar degrees. However, in real world networks, the degree distribution is relatively different. The majority of the nodes in real world networks usually have small degree and only few nodes contains large degree with many connections to other nodes. These large-degree nodes are often referred to as hubs, in analogy to supply chain networks where a few firms (hub firms) are connected to a very large number of other firms while some firms are connected to only a very small number of firms. Thus, it has been proposed that the degree distribution can be used to classify a variety of diverse real-world networks (Amaral et al., 2000). If we consider the undirected network $G = (N, L)$, the degree of a node i represent the number of connections that it contains (Boccaletti et al., 2006). In terms of the adjacency matrix A, a $N \times N$ square matrix whose entry $a_{ij}(i, j = 1, \ldots, N)$ is equal to 1 when the link l_{ij} exists, otherwise it is zero. The degree of node i is just the sum of the i^{th} row of A as shown in equation (1).

$$k_i = \sum_j a_{ij} \tag{1}$$

However, in the case of supply chain networks, it is necessary to define the network as directed. The directed network contains a more complicated degree distribution because the degree of a node in a directed network cannot be viewed as a single number. If we closely look a node in a directed network, we can easily figure out that there are some edges going out from the node and some edges coming into the node. Both the incoming and outgoing edges contains very different meanings, and this is a distinction worth keeping. One cannot just ignore these directions because material coming into a firm has a different value from material going out of a firm. Therefore, instead of just adding total edges, the incoming and outgoing edges must be added separately, from which the two numbers are obtained for the degree of a node. The *in-degree* of node i is the total number of connections onto node i, and is the sum of the i^{th} row of the adjacency matrix as shown in equation (2).

$$k_i^{in} = \sum_j a_{ij} \tag{2}$$

On the other hand, the *out-degree* of node i is the total number of connections coming from node i and is the sum of the i^{th} column of the adjacency matrix

$$k_i^{out} = \sum_j a_{ji} \tag{3}$$

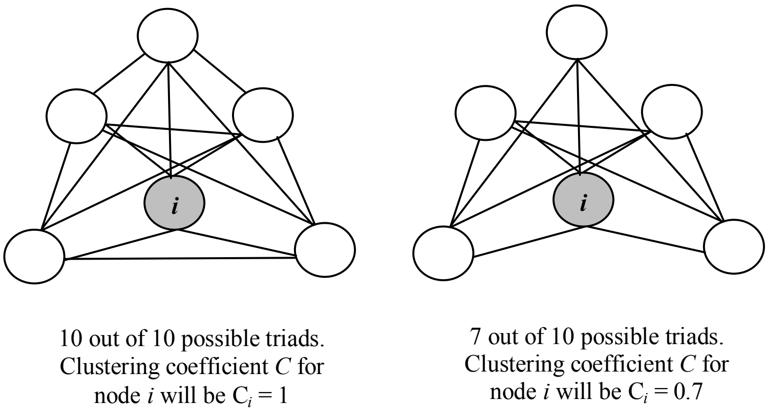
In both cases, the sum is over all nodes j of the network. We can add equations (2) and (3) to get the total number of connections of a node, or its total degree.

$$k_i^{tot} = k_i^{in} + k_i^{out} \tag{4}$$

The clustering coefficient is a property of a node in a network. Roughly speaking, it tells how well connected the neighbourhood of the node is. If the neighbourhood is fully connected, the clustering coefficient is 1 and a value close to 0 means that there are hardly any connections in the neighbourhood. The clustering coefficient expresses network transitivity, which is the average probability of two neighbouring nodes that are connected to a given local node being also connected to each other. In a supply chain network, clustering coefficient represents the triadic connection where two of the firms which may be supplier of hub firm also have connections with each other. This concept is traditionally called supply chain integration and due to complex and uncertain environment, the smooth flow of information among supply chain members is essential for competitive supply chain (Pujara and Kant, 2013). The clustering coefficient is the ratio between the actual close triads and total number of possible close triads of a supply chain network, as shown in Figure 2. Mathematically the ratio between the number of existing (E_i) of edges that actually exist between degree (K_i) of nodes and the total number of K_i (K_i − 1)/2 gives the value of the clustering coefficient (C) of node i as shown in equation (5).

$$C_i = \frac{2E_i}{k_i\left(k_i - 1\right)} \tag{5}$$

Figure 2 Clustering coefficient determination for node (firm) *i*



Currently, complex network theories offer random-graph, SW, and SF networks which are most likely to be used to design supply chains. Following section briefly describes these network models.

Random Erdos-Renyi (*ER*) *graphs,* which are initially created by a disconnected set of nodes that latterly combine with a uniform probability. In such random networks, the majority of the nodes contain the same number of connections, which shows that they have low heterogeneity and the degree distribution of such random networks will be a Gaussian bell-shaped curve. The resulting random graph after applying the ER algorithm will contain low clustering and short average paths.

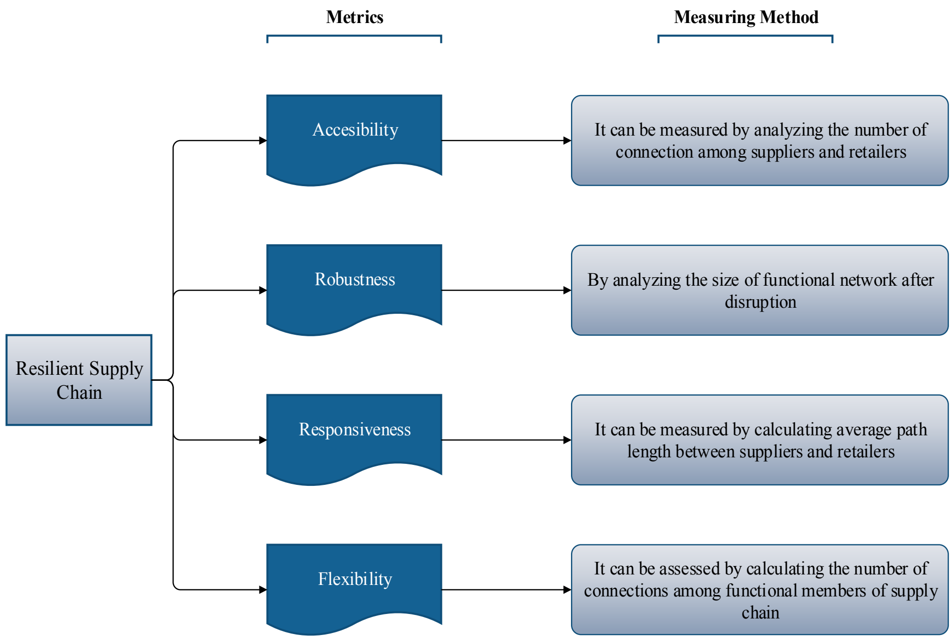
After the random graph, the next model is proposed by Watts and Strogatz (1998), in which they have rewired the connections between the nodes in a regular graph with a certain probability. The resulting graph is referred to as *SW network,* whose structure is in between the regular and random graphs. The structure of SW networks are very similar to many social networks, they contains the average path with same number of edges and nodes with higher clustering, which is almost similar to the random networks. Usually high modularity is found in small world networks, where some groups of nodes are more tightly connected with each other than the rest of the network.

Finally, the third category of networks are *SF* networks, which follows a 'power-law' with a degree distribution that is highly heterogeneous (Barabasi, 1999). They are named as scale free because if we focus on any part of the distribution, the shape remains same. In such networks, the nodes are few but significant in number with a lot of connections, and there is a trailing tail of nodes with a very few connections at each level of magnification. There is a sufficient argument that supply chain network follows a SF power-law degree distribution (Hearnshaw and Wilson, 2013), where a small number of firms (hub firms) have a large number of connections and a large number of firms (preferential firms) have a small number of connections. It is true for real world supply chain that hub firms made large connections with many suppliers and distribution centres, while these suppliers or distribution centres have connections with only few hub firms.

4 Resilient supply chain network metrics

It has been argued through an interdisciplinary review of the complex network literature that the properties of complex network models are applicable to real-world supply chains (Hearnshaw and Wilson, 2013). However, it is necessary to analyse these complex network models for designing resilient supply chain. From a complex network perspective, various resilience metrics are developed for supply chain network (see Figure 3).

Figure 3 Resilient supply chain metrics (see online version for colours)



In order to illustrate the resilience metrics mathematically, consider the supply chain network as an undirected network graph $G(V, E)$ where V is the set of nodes and E is the set of edges where $e_{i,j}$ represent an arc between node v_i and v_j. In a supply chain configuration V is the superset of V_s as set of suppliers, V_m as set of manufacturers, and V_r as set of retailers as shown in equation (6).

$$V = V_s \cup V_m \cup V_r \tag{6}$$

Equation (7) the network connectivity, i.e., set of retailers should be connected with set of suppliers through manufacturing units. Therefore, the set of retailers V_r (demand nodes) that have excess to set of manufacturing unit V_m and set of supplier V_s in the network is defined as shown in equation (7) where $p_{i,j}$ denotes the path between nodes v_i and v_j, $p_{j,k}$ denotes the path between nodes v_j and v_k.

$$V_{rms} = \left\{ v_i \in V_r \mid \exists \ v_j \in V_m : \exists p_{i,j} \text{ and } v_j \in V_m \mid \exists \ v_k \in V_s : \exists p_{j,k} \right\} \tag{7}$$

One of the most important strategy for designing robust supply chain network is *accessibility*. It enables the firms to respond to market demand quickly during major disruptions (C. S. Tang, 2006). Supply chain risk increases with lack of supply accessibility (Lin and Zhou, 2011), therefore, high supply accessibility guarantees the resilient supply chain network. Supply accessibility can be measured by analysing the total number of demand nodes (retailers) connected with supply nodes (suppliers). Therefore, supply availability is defined by equation (8), i.e., percentage of retailer nodes that have access to supplier nodes through manufacturing nodes.

$$S_A = |V_{rms}| / |V_r| \tag{8}$$

Second key criteria to design resilient supply chain network is *robustness* because it enables firms to deploy the associated contingency plans efficiently and effectively when facing a disruption (Tang, 2006). Supply chain robustness is the ability of supply chains to maintain its functions during random and targeted disruptions (Btandon-Jones et al., 2014) and it can be achieved through resilience (Pettit et al., 2010). Robustness of network can be measure by estimating the size of largest functional network after disruption.

It is important to note that resilience is a superset of survivability. It is the capability of a system to fulfil its mission, in a timely manner, in the presence of threats such as day-to-day operational threats or large-scale natural disasters/low probability and high impact events (Mohammad et al., 2006). The most important topological metric is the robustness of network, i.e., how much percentage of firms still active after certain disruption in supply chain network, which is the ratio between the sets of all available nodes V to the set of existing node V_n such that there is at least one supply node and a path between supply node to set of retailers. However, this is under the assumption that demand can be satisfied through existing supply nodes. After disruption, the supply chain network may breakdown into several sub networks. Thus, the remaining functional network (RFN) is $G_n(V_n, E_n) \in G_{sub}$ (G_{sub} is the set of all remaining functional sub networks), which should satisfies requirements as shown in equation (9), which means that all nodes in the network should be connected such that there exists at least single manufacturing node and single supplier node assuming that demand of retail nodes v_i can be fulfilled by available supplier node v_k and manufacturing node v_l. Therefore, the robustness of network can be measured by finding out the size of largest functional supply chain network $G'_{LFN}(V'_{LFN}, E'_{LFN})$ after disruption as shown in equation (10).

$$\forall v_i, v_j \in V_n : \exists p_{i,j} \text{ and } \exists v_k \in V_n : v_k \in V_s \text{ and } \exists v_l \in V_n : v_l \in V_m \tag{9}$$

$$\begin{aligned} &G'_{LFN}\left(V'_{LFN}, E'_{LFN}\right) \\ &= \left\{G_n(V_n, E_n) \in G_{sub} \mid \forall G_o(V_o, E_o) \in G_{sub}(n \neq o) : |G_n(V_n, E_n)| \geq |G_o(V_o, E_o)|\right\} \end{aligned} \tag{10}$$

Third important criteria to design resilient supply chain network is *responsiveness*. In today's competitive business environment one cannot ignore the responsiveness of supply chain (Shahin and Azar, 2013), therefore, it is also necessary to measure the supply chain responsiveness after disruption in order to know how well supply chain can respond in crisis situation. The responsiveness can be measured through supply path length, i.e., small supply path insures high responsiveness as least number of intermediaries exists between supplier and retailer reducing the lead-time. The average of the *minimum supply path length* between all pairs of suppliers-manufactures and all pair of manufactures-retailer will be the *average supply path length* in the largest functional supply chain network as shown in equation (11), where $d(v_i, v_k)$ represent the distance between retailer nodes and supplier nodes.

$$SPL_{avg} = \frac{\sum v_i \in V_{Lr} \sum v_k \in V_{Ls} d\left(v_i, v_k\right)}{|V_{Lr}| \times |V_{Ls}|} \tag{11}$$

where

$$V_{Lr} = V'_{LFN} \cap V_r \ , \ V_{Ls} = V'_{LFN} \cap V_s$$

The fourth key criteria for designing resilient supply chain is *flexibility* which enable firms to shift the production among suppliers promptly, and it also enables them to rapidly change the transportation mode (Tang, 2006). Flexibility can be assessed by estimating the clustering coefficient of the network as it computes the number of triadic connections in the network. Increases in clustering will increase the flexibility in the largest functional networks $G'_{LFN}(V'_{LFN}, E'_{LFN})$, thus leading to highly flexible supply chain networks. The clustering coefficient of node i can be defined by equation (12). Table 1 summarises the resilient metrics for supply chain network.

$$C_i = \frac{2E'_{LFN}}{k_i\left(k_i - 1\right)} \tag{12}$$

Table 1 Resilience metrics for supply chain network

Name	*Topology level metric*	*Description*
Accessibility	Supply availability rate	The percentage of retailer nodes that have access to manufacturers and suppliers [equation (8)].
Robustness	Size of largest functional supply chain network (LFN)	The number of nodes in the remaining network, in which there is a path between any pair of nodes and at least one supplier and manufacture satisfying demand [equation (10)].
Responsiveness	Average supply path length in largest functional supply chain network (LFN)	The average of the shortest path length between any pair of supplier and retailer nodes [equation (11)].
Flexibility	High clustering coefficient	The ratio between the number of edges among a node's first neighbours and total possible number of edges between them [equation (12)].

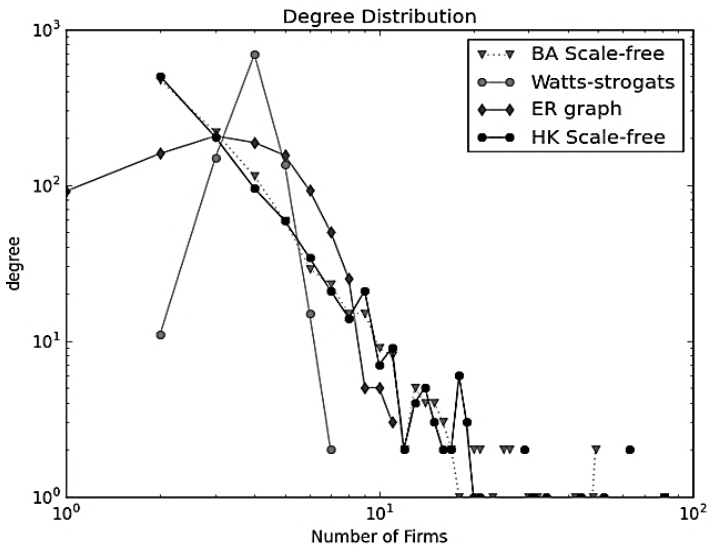
5 Experimental analysis

We have to rely on computer simulation as the real world supply chain cannot be constructed to analyse a disruption within it. In this section, the above developed resilience metrics are analysed on various complex network models to evaluate the resilience of supply chain network based on these complex network models. As discussed earlier, most common complex networks: random graph, SW and SF can be used to design a real-world supply chain. Therefore, for analysis purposes we use these complex networks to measure the applicability for designing resilience of supply network.

The size of real-world supply chains vary with respect to organisation types and their function. The number of nodes and edges in supply chain vary from 8 to 2,025 nodes and 10 to 16,225 edges (Willems, 2008). For simulation purposes, we chose a dataset with 1,000 nodes and 1,815 edges with average degree is about 3.6 is considered. Retailers, manufacturers, and suppliers enter the system following a ratio of 50:1:10. In other words for fifty new retailers, one manufacturer and ten suppliers are required to be added in supply network. Python-based module *Networkx* was used to measure the developed resilience metrics and for implementing the algorithms of complex network models. For analysing disruptions in the supply chain network, a randomly chosen node was removed in random disruption while a highly connected node was removed in targeted disruption in each step of the simulation. This simulation process continues until the condition of functionality fails as defined in equation (9).

We consider two different scale free algorithms for analysing a resilient supply chain, i.e., BA-scale free developed by Barabasi (1999) and HK-scale free developed by Holme and Kim (2002) because of the different clustering coefficient properties. It can be noticed from Figure 4 that degree distribution of ER graph and Watts-Strogatz network follow approximately Poisson distribution, whereas BA SF and HK-Scale free follows power law degree distribution. As discussed earlier, efficient and resilient supply chain follow power-law degree distribution as hub firms have more number of relations than peripheral firms. This shows that ER graph and Watts-Strogatz network models are less useful as compared to SF models, however it is necessary to check the other resilient metrics of these network models as it give more insights for designing resilient supply chain network.

Figure 4 Degree distribution of network models



One of the important resilient metric is flexibility of supply chain network that can be measured by clustering analysis [see equation (12)]. High clustering coefficient means that supply chain can perform under high threats as firms can share the losses with each other easily, which results less destruction of supply network as whole. On the other hand, those supply chain which works on low clustering coefficient are destroy easily because of less relations with each other. Figure 5 shows clustering analysis of complex network, which shows that average clustering coefficient of Watts-Strogatz model is highest among others, while ER graph network has least clustering coefficient. Both SF networks show less clustering coefficient than WS model which means that they are less competitive than WS network. However HK SF network provide much improved clustering coefficient over BA SF model, which shows that supply chain may be designed as more resilient and flexible network with HK SF model.

Figure 5 Average clustering coefficient of supply network under different complex network models

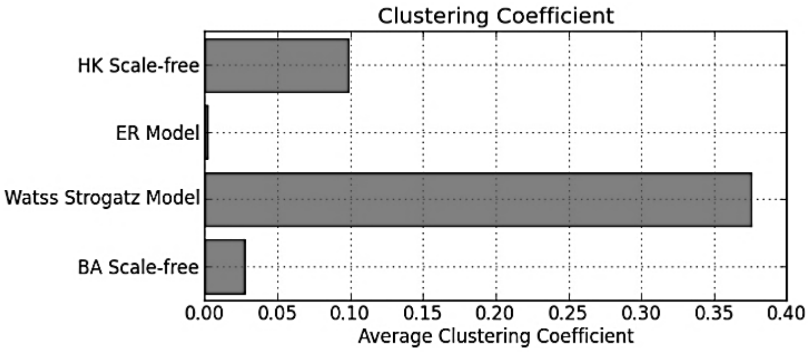
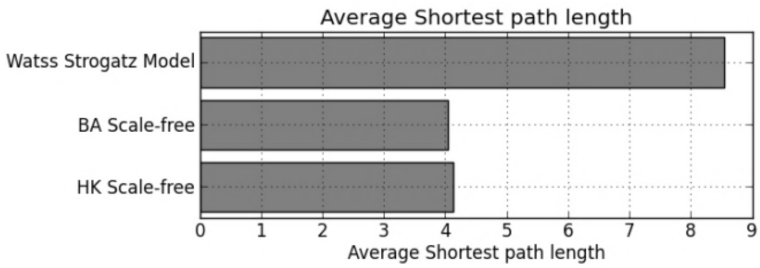
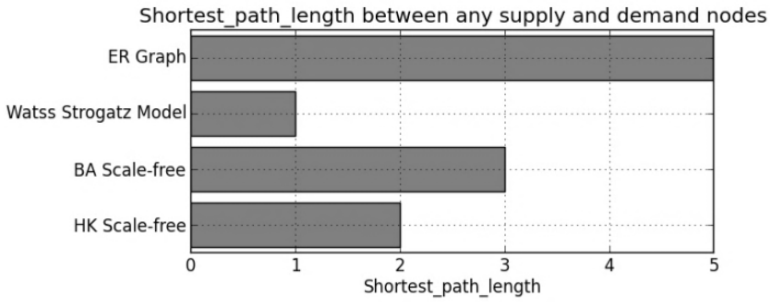


Figure 6 Average shortest path length of supply chain network



The competitive business environment needs responsive supply network. Responsiveness is one of the main resilient metric for supply network. The average shortest path length between any pair of supply and demand node should be minimum for high responsive supply chain network [see equation (11)]. Figure 6 shows average shortest path length of supply chain network designed using different complex network models, which represents that SF network has shortest path length it is good sign for designing resilient and responsive supply chain network. However average shortest path length of ER graph cannot be calculated as these network not have always connected nodes. It is also necessary to analyse the shortest path length between any pair of supplier and retailer nodes, shortest path between supply and demand nodes represents highly resilient supply chain network as the probability of supply availability is always high even after destruction of some nodes/firms in the supply chain network. Figure 7 shows average path length between any pair of supplier and retailer node. The result shows that ER graph have highest path length between supply and demand nodes hence not suitable for designing responsive supply chain, whereas Watts-Strogatz model have minimum shortest path length.

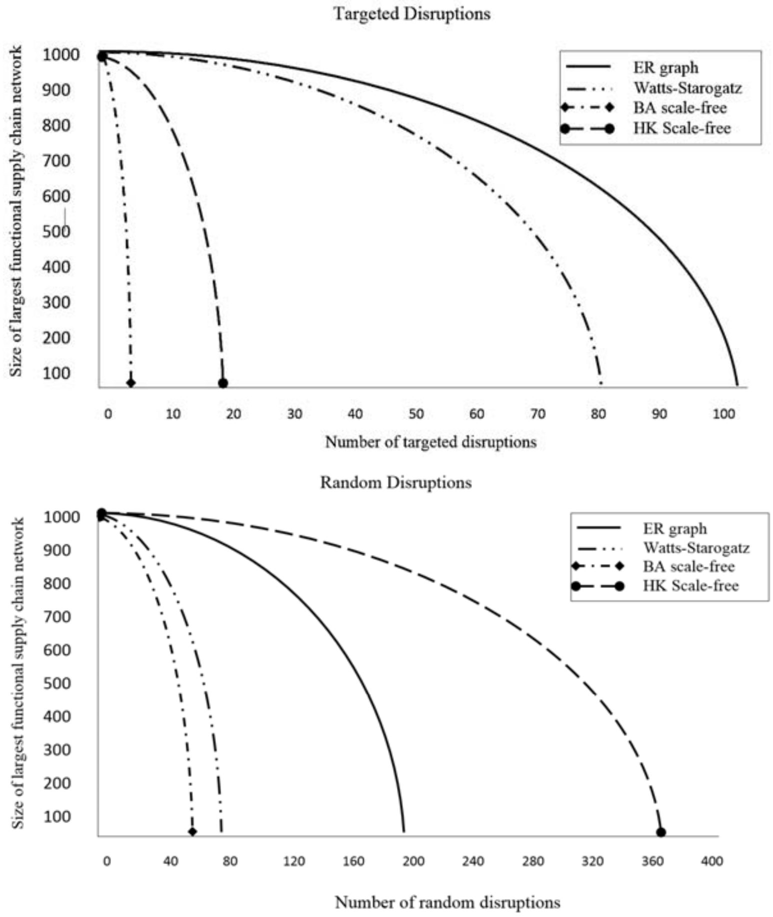
Figure 7 Shortest path length between supply and demand nodes



The robustness of supply chain network is analysed based on equation (10). Various complex network models are studied as shown in Figure 8. It can be noticed that ER graph and Watts-Strogatz models show similar results for targeted and random disruptions as these both networks give high robustness in targeted disruptions while medium robustness in random disruptions. This is because they consider all nodes equally. However BA model gives surprising result for random disruptions as it is less robust than Watts-Strogatz model contrary to previous studies results (Albert and Barabasi, 2002; Hearnshaw and Wilson, 2013), this is because of conditions defined in equation (9). BA model in random disruptions usually choose preferential firms first and then hub firms. Condition defined in equation (9) restricts that there should be some suppliers and manufacturer available in remaining functional network, but in random disruption suppliers as a preferential firms are removed in initial few attacks/disruptions. Therefore, BA model shows less robustness against both random and targeted disruptions.

On the contrary, HK SF model developed by Holme and Kim (2002) shows high robustness against random disruptions because of its tuneable clustering coefficient property. High clustering coefficient makes supply chain more flexible, and it can survive for more time than a low clustering coefficient. Also, the supply availability during disruptions increases the chances of survivability. Supply availability rates are analysed based on various complex network models, as shown in Figure 9. It shows the same results based on reasoning discuss above as supply availability depends on existence of suppliers and manufacturers in RFN [see equation (7)]. If number of supplier and manufacturing nodes increases then obviously supply availability will also increase.

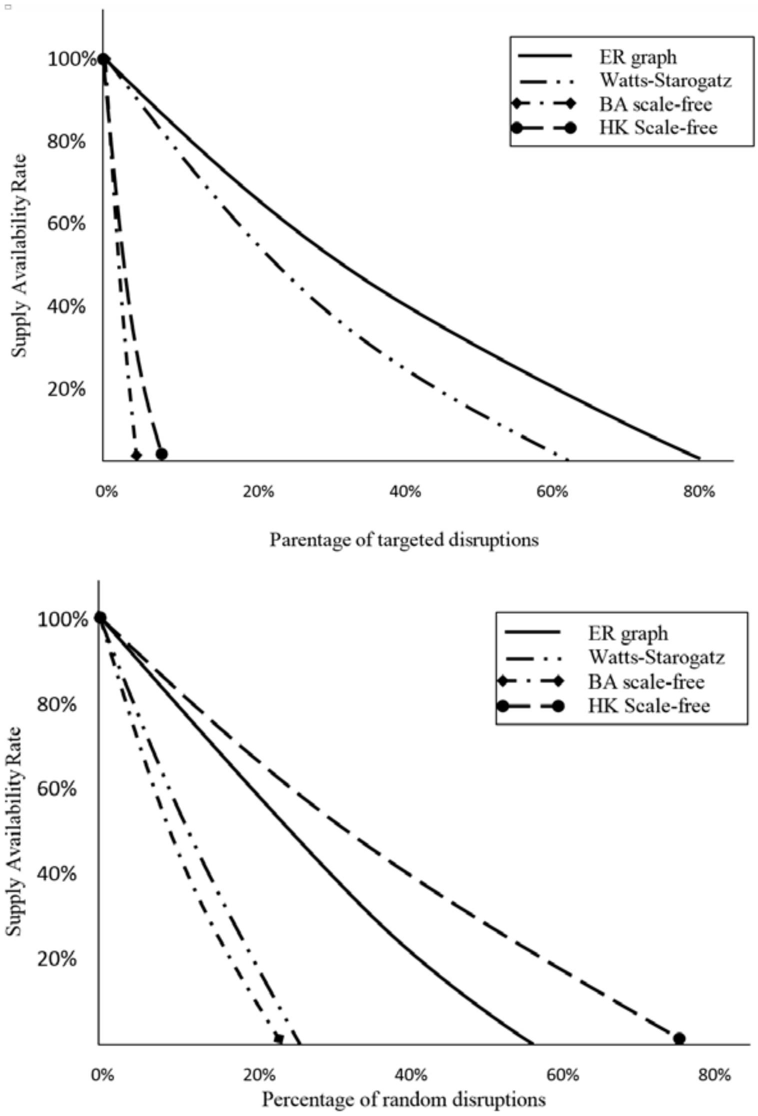
Figure 8 Size of largest functional supply chain network after random and targeted disruptions



The random network (ER graph) properties do not match the required resilient supply chain network because it contains low clustering coefficient making it less resilient to random and targeted attacks/disruptions. The next SW network proposed by Watts and Strogatz (1998) gives acceptable results in terms of clustering coefficient and short characteristics path length for designing resilient supply chain, because it gives high clustering coefficient and short characteristics path length between any pair of supply and demand nodes. The resilient supply chain requires the same properties as short characteristic path length in information flows indicates that the supply chain is able to diffuse and circulate information rapidly throughout the entire system, which facilitates more efficient material and financial flows, More efficient supply chain could be achieved by increasing its clustering coefficient by deliberately forging new horizontal connections, but when we look into the degree distribution of Watts Strogatz model, it does not show supply chain network.

As discuss above, the efficient supply chain hold power law connectivity distribution as there are few firms having large number of connections called hub firm while some have low number of connections called peripheral firms. Therefore, WS model gives disappointing results for designing the resilient supply chain network because it does not follow power law degree distribution. Hence SF network model is only network model to date which may represent supply chain network structure because of its degree distribution.

Figure 9 Supply availability rate under targeted and random disruptions



The properties of BA SF network also do not completely match with resilient supply chain network as it has low clustering coefficient which is opposite to resilience phenomena. The BA SF model was further studied by various researchers including Holme and Kim (2002). They develop a growing SF network with SW behaviour referred here as HK SF model, which shows short characteristic path length and high clustering coefficient. HK SF model represent real world supply chain better than any other model discussed here. However Hearnshaw and Wilson (2013) criticise the SF network for designing supply chain network because of the following reasons.

- The growth phenomena of SF model is not true in all cases, for example mature supply chains systems with many old firms are likely to have relatively fixed number of firms for long period of time.
- The preferential attachment assumes that the new relationship by a firm is totally depend on existing relationship between the firms. However, one can imagine examples where older, more established firms have been usurped by new entrants.
- Efficient supply chain systems demonstrates a 'fit-gets-richer' mechanism of growth, while SF network shows 'rich-gets-richer' phenomena.

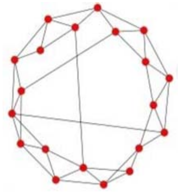
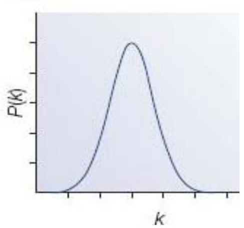
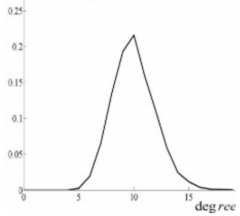
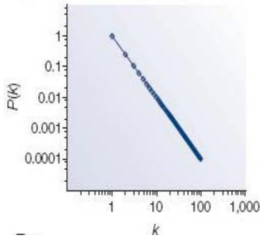
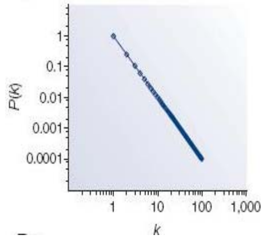
Consequently like other models, SF model, does not provide all the required properties to design resilient supply chain network. It is also found here that SW and ER models are highly robust to targeted attacks while less to random attacks. On the other hand BA SF model is less robust to random attacks and poor to targeted attacks. The SF model developed by Holme and Kim (2002) gives improved results when compared to other network models. However it is not possible to use directly these networks to design resilient supply chain network as properties of SF network mismatch with real world supply chains. Thus, while complex network models provide basis for designing supply chain, we can, however use their evolution principles to design an efficient and resilient supply chain network. Table 2 summarises the comparison of existing complex network models to resilient supply chain.

6 Conclusions

This paper analyse the statistical mechanics of complex network and implements complex network theories for designing resilient supply chain network. The paper developed metrics for designing the resilient supply chain network, which will be helpful for practitioner and researcher for further development of more resilient supply chain network. The model provide insights for practitioners of all kind of supply chain network to analyse the relationship with their suppliers and other firms present in their supply chain. They can analyse various disruption's effects on their supply chain structure which surely gives gainful results.

It has argued through an interdisciplinary review of the complex network literature that the properties of complex network models are applicable to real-world supply chains. We have reviewed major complex network models, and result shows that properties of resilient supply chain network can be mirrored by SF network. While it has been argued that SF networks appears to represent efficient and resilient supply chain systems, SF model also cannot be applied directly to design efficient supply chain network as SF network works on the rich-gets-richer phenomenon, while efficient supply chain systems demonstrate a 'fit-gets-richer' mechanism of growth. Therefore, to-date there is not a single complex model which can represent resilient supply chain network. Based on results of this paper, the future research is to design the SF network that can better represents the efficient and resilient supply chain.

Table 2 Comparison of resilient supply chain and complex network models (see online version for colours)

	Efficient and resilient supply chain	*Random* 	*Small-world* 	*BA-scale free* 	*HK-scale free* 
Degree distribution	Power law	Normal/Poisson 	Depends on $P_{deg}(k)$  Linearly with N for small $P_{deg}(k)$ $\log(N)$ for higher $P_{deg}(k)$	Power law 	Power law 
Characteristic path length	Short	Short	Short	Short	Short
Clustering coefficient	High	Low	High	Low	High
Robustness to disruptions	Should be highly robust to random and targeted attacks	Similar response to random and targeted attacks	Similar response to random and targeted attacks	Less robust to random attacks and poor to targeted attacks	Highly robust to random attacks but poor to targeted attacks

The above discussion shows that research in complex networks as applied to the context of supply chains is far from complete. There is extreme need of further research in this area to development more robust network models that can represent efficient and more resilient supply chain networks. It can be seen that the models presented here ignored the capacity constraint on vertices (firms) and edges (transport). Therefore, the next study in this area is to incorporate the capacity constraints as removal of highly weighted supplier can disrupt the entire supply chain network. Also, in this study disruptions at firms are analysed but analyse the disruption of edges would also be an interesting area of research. This may be fruitful because during random disruption, transportation system may be interrupted because of any natural or man-made disaster.

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