CRANFIELD UNIVERSITY

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USING NETWORK SCIENCE TO DISENTANGLE SUPPLY NETWORKS: AN EXAMPLE IN THE AEROSPACE INDUSTRY

SCHOOL OF APPLIED SCIENCES

MSc THESIS
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This thesis is submitted in fulfilment of the requirements for the degree of Master of Science

ABSTRACT

Supply chains in the aerospace sector are becoming more complex than ever before, frequently causing delays on the production process. Complexity gave rise to the term “supply networks”, changing the way we view supply chains from a structural point of view. Structural properties are important to investigate as they help define robustness and efficiency of systems. Although complexity in structure is suspected by previous researchers who studied these networks, empirical data to characterise what complexity means, and how it effects properties of networks has been largely absent from literature. If empirical data is available, network science can be used to understand structural properties of such complex supply networks. Network science is a suitable Mathematical tool for analysing the complex relationships and collaborations in the network and summarizing the properties of network from a fundamental, structural perspective. In this report, the author will apply network science to analyse the structure of the Airbus supply network. Due to the lack of aerospace supply chain data, firstly an empirical database is built. Analysis then focuses on the real structure of Airbus supply network and identification of key firms or communities under two scenarios: *a non-weighted network* in which the value of link is either 1 or 0, and a *weighted network* in which the value of link presents the strength of relationships among firms. While the weighted network indicates more informed features of the supply network structure by considering the weight of relationships, the non-weighted network can help us understand fundamental patterns that determine the structure of the connections in the network. The analysis indicates the Airbus supply network carries a power law distribution, which means most resources are dominated by few firms, and the network is robust to random firm failure but vulnerable to hub failure. The network contains communities with strong relationships between them. These communities do not only belong to the same industry and same region but have emerged as the result of an interaction between the two effects. Some key firms in the network own significant power of control the supply chain and financial resources, occupying key positions that bridge communities in the network. The study presents key structural features of a large scale network using empirical

data and act as a case example for using network science based analysis in supply chains.

Keywords:

Aerospace supply chain; network science; Empirical data; Weighted network; Robustness

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LCC	Largest connected component
Nadcap	National Aerospace and Defence Contractors Accreditation Program
QOS	Quality of Service
SNA	Social Network Analysis

1 Introduction

Throughout the development of technology and the world economy, globalization and multinational operations are increasing rapidly(Prasad and Babbar, 2000). Before a product is brought into the market, a number of firms are involved in the product manufacturing process to form a complex product through the supply chain network. Nowadays supply chain issues receive more attention than ever before. Supply chain management covers almost all activities of firms, from product research and design, manufacturing, logistics, sales and customers. Actors in the chain could be manufacturers, service companies, and public organizations. These actors connect to one another to procure goods and services, yet do not know with whom their direct connections are connected. As firms form connections, chains emerge, which are largely invisible to the companies involved in them. The emergent formation of the chain causes two key problems. The first one is that firms cannot see their positions in the whole supply network; they can only see the observable flow of products directly connected them. Even when companies are aware of the chain, they attempt to reduce the complexity by reducing the number of suppliers and simplifying the transactions between the suppliers (Gattorna, 2006). This strategy seems to make the supply chain even more vulnerable to failures, such as logistics failures, suppliers going bankrupt and natural hazards (Cheng et al., 2014).

Aerospace manufacturing industryneeds international cooperation but also more reliable supply, thus the supply chain is a key factor in maintaining aerospace manufacturing order and gaining profits. There is an increasing awareness that supply chain management skills have become more significant. 65%-80%of the final cost of aerospace production is dedicated to suppliers; however the delay of programmes were also caused by suppliers (Tang et al., 2013). For example, in October 2007 Boeing embarrassingly reversed its promise of delivering the first Dreamliner jet, due to the shortages of key materials and slow deliveries by suppliers (Lunsford, 2007). Similar supply chain problems also occur in the automotive industry. Some of the more recent notable cases included the March 2011 the Tohoku earthquake, which damaged supply chains heavily, causing a drop of over 30% of the daily global automotive production (Brintrup, 2014). Although it is imperative to understand the structural properties of aerospace supply chains, there have been no studies so far for there was a lack of data on the emergent chain which can weave a network.

While researchers understood the importance of studying emergent structures of supply chains, and dubbed them as complex networks (Kim and Choi et al, Gunasekaran et al, Borgatti), network science has been gaining attention as a significant mathematical tool to analyse the structural features of networks. Network science can approach the characteristics of several real work systems by abstracting them as nodes and connections between them. As a tool it can form useful individual and overall views of how these systems function (Fan and Liau, 2014). A number of researchers applied it in many diverse fields, including protein structures, airport transport networks and disease transmissions (Amitai et al., 2004; Lordan et al., 2014; Valentini et al., 2014). Kito et al. (2013) presented the supply network structure of Toyota by applying the theory of social network analysis in the automotive manufacturing industry.

To carry out network analysis, it is necessary to define a network in the aerospace sector. A node or a vertex here can be depicted as a firm, and a link or an edge is the supply-buy relationship between firms, the direction of which determines who buys from whom. A weighted network is defined where a link between firms represent the strength among the nodes in the network. For example, it can denote the frequency of contact between people in human social networks; or it can present the transaction value among suppliers and customers in supply networks. In a supply network the weight can highlight the significance of the buy-sell relationship between firms, such as volume of transactions, or price as percentage revenue. By using such analysis, fundamental properties such as robustness can be investigated, which can indicate the how strong the network is to the failure of individual firms or communities. The power of network science as a tool to understand robustness in complex systems, and the recently highlighted vulnerabilities of complex supply networks have been the motivation behind this study.

The contribution of this thesis to the complex supply network debate is threefold: First, empirical data has been lacking from complex supply network literature. We help close this gap by collecting and using large-scale data that characterises the aerospace supply chain of a major company. Second, we apply network science to supply networks, a new domain of application that has not been studied by network science before. Thirdly, this study provides valuable insights into the structural properties, and in particular robustness of the aerospace sector by providing a case study. The case study company we use is the Airbus Group (Airbus hereafter).

Airbus is a major aerospace manufacturing firm, who has suppliers around the world. Given its scale, and availability of data, Airbus presents a unique case that can be used to gather statistically significant insights.

In the rest of this thesis, network science is applied to investigate the Airbus supply network to discover the properties of its structure and individuals' positioning within its structure.

The structure of this thesis is organized as follows: section 2 reviews the relevant literature to find out the research gap and states the aim and objectives. In the section 3, the methodology addresses how the objectives and aim are achieved. Section 4 analyses and discusses the results. Finally section 5 states the conclusions and future research suggestions.

2 Literature review

There are five sub-sections in this section including a review of definitions of supply networks, a review of the aerospace supply chain, and analysis of networks using network science approaches, properties of networks such as robustness and finally research objectives and aims. The first sub-section describes the configuration and problems of Aerospace supply chain network. In the second sub-section, the relevant techniques used in network science are summarized through examples and empirical results. Section 2.3 states recent research in weighted networks and explain its relevance to this study. Section 2.4 describes robustness from a network science point of view. Then the application of network science in supply chains is introduced in section 2.5. Finally, section 2.6 outlines the research gaps and the objectives and aim of this thesis.

2.1 Aerospace industry supply network

The aerospace manufacturing supply chain has significantly changed in the past century, though the role of suppliers in the chain become more and more important all the time, thus the supply chain management is a fundamental capability for an aerospace manufacturing firm. In the early nineteen century, the dealings between suppliers and aerospace manufacturing firms are simple raw materials (Tang et al., 2013). From then on, there are some evolutionary phases can describe the process of aerospace supply chain revolution during 1910s to 1960s (Rose-Anderssen et al., 2009):

1) Local purchasing strategy introduced by Boeing-Westervelt;
2) Political knowledge sharing with outsourcing and subcontracting of aircraft section and system;
3) Subcontract of adaptable manufacturing technologies;
4) Local collaboration between suppliers and original equipment manufacturer (OEM).
5) Collaboration across national borders with multiple suppliers

A modern aerospace supply tactic to share risks and joint venture is started-off around 1975. When Airbus was introducing this strategy and competing with North American aerospace industry Boeing was insisting on OEM domination (Tang et al., 2013). But not soon after, Boeing launched Boeing 777 with this new modern supply chain strategy and Airbus with A340 as well during middle 19th century. In order to enhance the strength of chain between strategic partners and accustom the customer's culture, the final assembly firms like Airbus and Boeing, chose to collaborate with the suppliers in the customer's nation, thus the supply chains have been transformed from being simple material transactions to global supply cooperation (Tang et al., 2013; Rose-Anderssen et al., 2009).

An individual firm cannot handle the whole aerospace production technologies due to its complexity; therefore the capability of information management beyond itself becomes significant essential (Rebolledo and Nollet, 2011). The feature of technology-intensive and diversity in aerospace industry forces the main assembly firms count on the involvement and collaborations of partners and suppliers for aircraft design and sub-section manufacturing (Amesse et al., 2001). Hence the aerospace industry firms develop to subcontract a certain extent of design and manufacturing works, which are with low value or intra-organizational operations, to suppliers; only keep the core competencies (Williams et al., 2002). Since the suppliers obtain more responsibilities and sub-system order, they also need to breakdown the work and distribute them to next tier of suppliers; they start to manage their own supply chain as system integrators (Smith and Tranfield, 2005). Meanwhile some suppliers become more competitive and capable in the aerospace industry; the main assembly firms are dependent on few suppliers who can manufacture advanced components or sub-systems (Williams et al., 2002).

Major aerospace firms such as Airbus and Boeing experienced suppliers and customers in their newest A380 and B787 programs. However the delay of both programs was still happened caused by suppliers. For example, the first delivery of Dreamliner 787 was delayed by the shortage of fasteners, due to replacement of the thousands of temporary fasteners on the large composite structure manufactured in Japan, Italy and US, and the boosting production rate which the fastener industry cannot follow, and late start in tooling up to make unique fasteners (Wallace, 2007).

Although structure is an important feature of networks, to date there has been less than a handful of empirical works that study the structure of supply networks in the aerospace industry (Wu and Choi, 2009; Lomi and Pattison, 2006;Kito et al., 2013).

2.2 Network science approach

Social network analysis becomes a significant tool to analyse the empirical projects and reveal its structure features (Tonta and Darvish, 2010). The structure of protein can be presented by the complex network graph, which the node and edge denote the amino acid residues and their interaction respectively (Amitai et al., 2004). (Vishkaie et al., 2014) simulate airborne disease spread by using two aspects of complex network analysis, which are structure level and dynamics level. Network science has been used to manifest communities, friendships and communication patter(Koehly et al., 2003).Kito and Brintrup (2013) claim that network science reveals the heterogeneous composition of Toyota and identifies the key firms.

There are many metrics of network in terms of different concept of importance, though they can be divided in to two levels of metrics: the node level and network level. Node-level metrics measure how a single node is embedded in a network from that individual perspective, and network-level metrics calculate how the overall network is structured from the over-view perspective (Kim et al., 2011).

Node-level metrics

Node-level metrics focus on the extent of importance and centrality for a node in the network. The degree centrality, closeness centrality and betweenness centrality are applied most widely in empirical researches.

Degree centrality is always the beginning when studying networks (Freeman et al., 1979–1980; Newman et al., 2011). The degree of a node just equals the number of edges connected it, in directed networks the node will have In-degree and Out-degree whose value will depend on the edges' direction (Newman, 2010). The nodes with these three high degree centrality are playing totally different role in the network: the high degree nodes are a "Coordinator" who reconciles differences of members and works with them for a team goal; the high In-degree node is an "Integrator" who gathers different information and parts to create a product with high value; the high Out-degree node is an "Allocator" who distributes boundless and popular resources to many customers (Kim et al., 2011).

The measure of closeness centrality and betweenness centrality both depend on the length of paths in the network (Opsahl et al., 2010). Closeness centrality measures the extent of how close a node is to all the other nodes. A node with high closeness is much freer from others' affection and capable of much independent action (Newman, 2010). Betwnessness Centrality measures the extent to which a node lies on the path among the other nodes (Freeman et al., 1991), (Newman, 2010). The node with high betweenness centrality presents more abilities to smooth the process of exchange and makes the transmission more efficiently (Freeman, 1978–1979).

Comparing to the degree centrality, the nodes with high Closeness and Betweenness centrality play different roles in the network. High closeness centrality node is like a "Navigator" who stands at the centre of network and obtains various information very fast; high Betweenness centrality node looks like a "Broker" who connects the customers and suppliers together, and improves the intra-action by holding developed relationship network resources (Kim et al., 2011).

Network-level metrics

The network-level metrics give another view of whole network properties, such as density, average degree, average path length, largest connected component.

Network density defines as the number of total edges relative to the number of total potential ties in the network; it measures the extent of the overall connectedness and collaboration of network (Kim et al., 2011).Average degree is just an extent of degree centrality, which measures the mean degree of all nodes in the network, can be another approach to detect the connectivity of the network (Kim, H and Anderson, R., 2012).

The Largest component size can measure the extent of integrity of the network; normally it is filling with most of network, sometimes all of it. Usually it is calculated as the number of total connected nodes relative to the number of all nodes in the network (Newman, 2010).

Scale-free network and small-world network

The networks are called scale-free networks if its degree distribution is power law behaviour, hence corresponds to a straight line on a log-log plot, such as World Wide Web citation networks (Broder et al., 2000; Chen and Redner, 2010). Two features of scale-free network are: (i) new nodes are added continuously, the network expands; (ii) new nodes prefer to attach the sites that are well connected (Barabási and Albert, 1999). Thought perfect power laws will in principle only be observed in the limit of infinitely large networks, and for real-world networks such as supply chains finite-size effects will induce an exponential cut-off in the power law (Amaral et al., 2000). However perfect power laws will in principle only be observed in the limit of infinitely large networks, and for real-world networks such as supply chains finite-size effects will induce an exponential cut-off in the power law (Amaral et al., 2000). In the only large-scale empirical study done to date on supply networks, Kito et al (2013) showed that there was an exponential behaviour found in Toyota supply network, in which some firms retaining extensively more relationships than others, but a clear upper bound or capacity restriction on the extent of relationships holding. This was contrary to previous assumptions of authors who suggested sale-free network structures in supply chains (Thadakamalla et al 2004, Zhao 2009). An exponential degree distribution is typically observed in networks generated by a trade-off evolutionary process that involves nodes incurring costs for obtaining links (Amaral et al., 2000).

The small-world networks are much clustered in which the nodes have small average path length (as known six between each other); some researcher find out some network have this phenomenon, such as collaboration graph of actors, Seismic networks and Neuronal networks(Ferreira et al., 2014; Watts and Strogatz, 1998; Yu et al., 2013).

2.3 Weighted networks

Many empirical networks exhibit a large heterogeneity in term of the different intensity of each edge, thus a simple binary relationship, which is either on or off, cannot indicate the features of this weighted network (Barrat et al., 2004). There has been a growing demand for network measures the take consideration of tie weights, for the dichotomized network loses much information in a weighted network (Opsahl et al., 2010). In some circumstances, the link with a strength, weight or value can represent more information; such as the amount of data flowing along them in the internet, or representing the frequency of contact between people in social network (Newman, 2010). Yook et al (2001) argue that the weighted networks are the best model to describe biological, ecological and economic networks.Meanwhile, a number of researchers explore the properties of weighted networks, for example, the hierarchy and topological features, of traffic fluctuations (Opsahl and Panzarasa, 2009; Wang et al., 2012; Sun et al., 2014).

The definition for measuring the weighted network is different according to different empirical data under consideration. For example in the International Air Transportation network, weights represent the number of passengers among these flight routes; in the net work of scientists who submit papers, the weights represent the number of collaboration in writing paper among the scientists (Barrat et al., 2004). It though is not enough to show the structure features of a weighted network by just using these weight elements. Combining node common metrics, which are degree, both weights and closeness and betweenness, and weight can get better result of network analysis (Opsahl et al., 2010). The correlation between weights and centrality in non-weighted networks is significant for revealing the characteristics of the real network (Barrat et al., 2004).

2.4 Robustness of networks

The failure of networks can cause economic costs and have catastrophic implications. After the 2011 Japan earthquake, the automotive supply network was implicated, in Japan, Europe and North America, had to pause their production for a few suppliers damaged in the earthquake (Brintrup, et. 2014). In 2001, $2.6 billion was lost since the Code Red Virus incapacitated number of computer networks (Sydney et al., 2008).

The robustness of a network will decide if it can survive from network attacks, just like animals rely on the food chain (Sydney et al., 2008). The definition of robustness in complex networks is the extent of survivability in the condition of the component failures and ongoing attacks that remove nodes or links from the network (Sydney et al., 2008).

There are two main approaches to measure the robustness of network: the first one is detecting the connectivity based on the graph topology; the other is considering the service and throughput in term of the parameter of Quality of Service (QOS) (Sydney et al., 2008; Manzano et al., 2013). Brintrup et al. (2014) suggest that the overall resilience and robustness of a supply network can determined by the structural arrangement and production capability and measure them using product redundancy and product market share.

Airbus has requested suppliers to achieve the Nadcap (National Aerospace and Defence Contractors Accreditation Program) accreditations relevant to their field and cascade the requirement to their Sub-tiers, in order to improve the robustness form perspective of QOS (Airbus, April 2012). In this thesis, the connectivity analysis is used only, for there is no product flow in the dataset used.

Kim and Anderson (2013) argue that the best defence and attack strategies are balanced replenishment and removing the target with high degree or

Betweenness centrality respectively, by monitoring the largest connected component and average degree to analyse the connectivity of a network. Natural connectivity can characterize the properties of robustness in the weighted network by increasing the weight strategies to nodes with different degrees in the network, in which weights denote the multiple edges (Zhang et al., 2013).

Measurement of connectedness of network can reveal the properties of topological robustness and practical robustness of network through two edge removal strategy: random failure strategy and attack strategy; the results show scale-free network are vulnerable to attack strategy (He et al., 2009). The feature of community structure can be detected in most general weighted networks, which are constructed by the strong links and weak links; furthermore, the community structure appears to be fragmented more quickly by weak links failure rather than strong links failure (Riitta et al., 2007).

2.5 Complex network analysis in supply chains

Due to the firms' direct supply relationship with their supply partners and indirect interaction with their direct supply partners, the supply chain presents a network property (Bellamy et al., 2014; Choi et al., 2001). Many researchers have stressed the importance of considering supply chain ideas from a network perspective (for example, Easton and Axelsonn 1992; De Toni and Nassimbeni 1995;Lamming 2000). However, progress has been constrained by a lack of developed analytical tools to describe and interpret network structures. The last decade has seen the emergence of a substantial body of techniques under the broad heading of 'network science' (Watts 2003; Newman 2010) which has provided a substantial repertoire of tools for understanding the characteristics of complex networks; Choi et al (2001, 2009) have pioneered the application of the these ideas to supply networks (see Borgatti and Li 2009). Nevertheless, despite the progress made with these insights, research has been further constrained by the lack of substantial datasets. Empirical support for the actual structure of supply chain networks: 'maps' of supply chains based on field data.

Such empirical maps - showing who supplies whom - are almost entirely absent from literature (New 2004).

There are, however, some exceptions, and several of these are based on the automotive sector. There are three related empirical studies on supply chains comprising Choi et al (2001)'s efforts to map part of the Honda, Acura, Daimler Chrysler, which consisted of 70 members; Lomi and Pattison (2006)'s analysis of 106 automotive firms in southern Italy; and Keqiang et al (2008)'s examination of the Guangzhou automotive industry, consisting of 84 firms. Although these examples provide a much-needed glimpse at supply network maps, their relatively small-scale limits their usefulness for the development of theory.

2.6 Aim and objectives

From these reviews it is obvious that the aerospace supply chain network has become more complex over the years, and the competition of efficient supply chain management has turned intense among aerospace manufacturing firms all over the world. However, there is no study in researching aerospace supply chain from a network perspective, although the application of network theory and the use of large scale empirical data seem promising to uncover how the aerospace industry looks like and functions in terms of connections between firms. The features of the complex aerospace industry supply network could be measured using network science. Network science can reveal the structure and characteristics of aerospace industry supply network, including which firms are the most central in the network; what responsibilities the firms have or which roles they play; which kind of network it is; how robust the network is and what vulnerabilities of network are.

Firstly, the author thus will collect supply chain data and validate the data in the thesis. Yet the data collection need a start point of supply network, the point should be a typical aerospace manufacturing firm which has abundant supply chain data in order to draw a significantly large-scale supply network. The author chose the Airbus supply network as the objective, for Airbus is a large, successful aerospace industry firm with global supply chain, and total orders has reached 14,105 at the end of June 2014 (Airbus, 2014).

The Aim of this dissertation is thus to reveal the real structure of Airbus supply network and the properties of its robustness. The specific objectives to reach aim are as follows:

1. To collect and validate data of Airbus supply network:
   The data will be collected in empirical database, and validated by cross checking with other resources.

2. To model the network in terms of empirical data:
   The structural features of Airbus supply network will be observed, including its hierarchy structure, geography and sector structure, robustness properties and communities.

3. To apply weighted network analysis
   Using the revenue information in the network models network as a weighted network, find out the connection between topology and finance distribution.
4. To find out the key firms
   According to the robustness, community constitution and firms' metrics, key firms that play special roles in the networks will be highlighted.

3 Data and methodology

3.1 Data collection

Data are collected from publicly available sources. We decided to obtain data from only one database, managed by an independent agency (Bloomberg[1]). We choose Bloombergbecause it can provide a supply network view from aerospace industry for which a large sample size is obtainable. Such a large scale network gives us the ability to maximize the chances of identifying clear patterns. This database is comprehensive and offers consistency when compiling data.Given the large size of this company's supply network, the corresponding data are sufficient to derive statistical analysis.

Supply chain analysis, one of many modules in Bloomberg, provides the supply chain information of every listed firm in the market; including (a) name, (b) geographical location, (c) supplier's market capability, (d) relationship value, (e)resource, (f)sub-industry and (g) firm's description.

The period of data collection is from Nov 2013 to Feb 2014, and the procedure is given as below:

1) Create a supply chain database starting with AIRBUS.
2) Search for "AIRBUS" on Bloomberg supply chain database, which presents a supply chain chart of Airbus (see Figure 3-1), also gives a supply chain table (see Figure 3-2). All of these firms and their data elements (a-f) were added to AIRBUS database.
3) There are 332 suppliers of AIRBUS in the Bloomberg totally, which are from 48 different sub-industries in terms of Bloomberg grouping function, such as ADVERTISING, AEROSPACE & DEFENSE,AIR FREIGHT & LOGISTICS and CONSUMER FINANCE, etc. The boundary should be restricted to 8 sub-industries (see Table 3-1), since the objective of the dissertation is focusing on the aerospace manufacturing supply chain.

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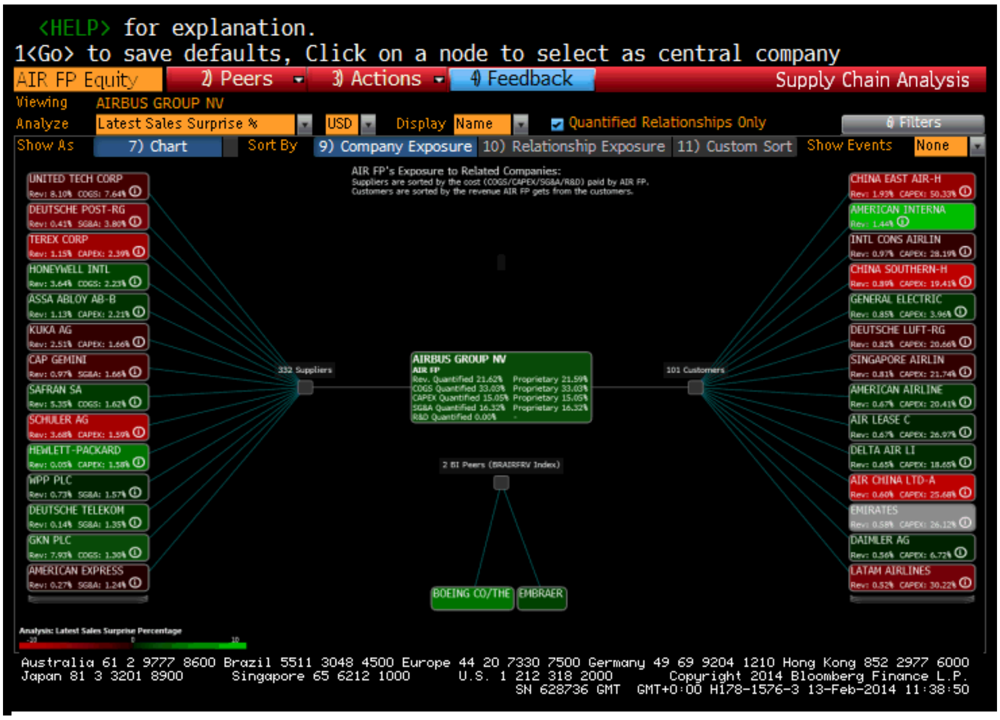

Figure 3-1 Airbus supply chain chart

(Airbus is in the centre of the figure, it is connecting with the 322 suppliers on the left and 101 customers on the right. The peers Boeing and Embraer are at the bottom of the figure)

<HELP> for explanation.
1<Go> to save defaults, Click on the data columns to see more information

AIR FP Equity | 2) Peers | 3) Actions | 4) Feedback | Supply Chain Analysis

Viewing AIRBUS GROUP NV

Analyze Latest Sales Surprise % | USD | Display Name | Quantified Relationships Only | 6) Filters

Show As 7) Chart | View 9) Suppliers | 10) Customers | 11) Peers

<Add Column, e.g. P/E> | 12) Fields

Name	Country	Market Cap	Sales Surprise	%Revenue	Relationship Value (Q)	Account As Type	%Cost	Source	As Of Date
21) AIRBUS GROUP NV	FR	57.30B	2.19%						
22) UNITED TECH CORP	US	104.22B	-1.87%	9.76%	1.64B	COGS	10.63%	Estimate	02/10/2014
23) DEUTSCHE POST-R	DE	43.62B	-4.68%	0.41%	75.79M	SG&A	3.80%	Estimate	01/13/2014
24) TEREX CORP	US	4.88B	-7.15%	1.15%	22.42M	CAPEX	2.39%	Estimate	01/13/2014
25) HONEYWELL INTL	US	74.19B	1.84%	3.64%	343.04M	COGS	2.23%	Estimate	11/01/2013
26) ASSA ABLOY AB-B	SE	19.45B	0.96%	1.13%	20.72M	CAPEX	2.21%	Estimate	01/13/2014
27) KUKA AG	DE	1.69B	-0.48%	2.51%	15.59M	CAPEX	1.66%	Estimate	01/13/2014
28) CAP GEMINI	FR	11.79B	-1.95%	0.97%	33.18M	SG&A	1.66%	Estimate	01/13/2014
29) SAFRAN SA	FR	31.18B	1.39%	5.35%	254.55M	COGS	1.62%	Estimate	01/21/2014
30) SCHULER AG	DE	1.15B	-7.77%	3.68%	14.89M	CAPEX	1.59%	Estimate	01/13/2014
31) HEWLETT-PACKARD	US	57.11B	4.66%	0.05%	14.79M	CAPEX	1.58%	Estimate	01/13/2014
32) WPP PLC	GB	30.59B	0.12%	0.73%	31.26M	SG&A	1.57%	Estimate	01/13/2014
33) DEUTSCHE TELEKOM	DE	73.66B	1.87%	0.14%	26.80M	SG&A	1.35%	Estimate	01/09/2014
34) GKN PLC	GB	11.36B	2.12%	7.93%	211.63M	COGS	1.30%	Estimate	12/03/2013
35) AMERICAN EXPRESS	US	94.70B	-0.08%	0.27%	24.67M	SG&A	1.24%	Estimate	01/13/2014
36) BRIDGESTONE COR	JP	29.35B	0.66%	2.01%	167.67M	COGS	1.13%	Estimate	12/11/2013
37) NEUSOFT CORP-A	CN	3.16B	-1.00%	3.71%	10.55M	CAPEX	1.13%	Estimate	01/13/2014
38) SODEXO	FR	16.27B	-0.16%	0.34%	20.76M	SG&A	1.04%	Estimate	01/13/2014
39) KUEHNE & NAGEL-R	CH	16.15B	-4.88%	0.43%	20.46M	SG&A	1.03%	Estimate	01/13/2014

Figure 3-2 Airbus supply chain table

(Figure 3-1 shows each supply chain's details including Name, Country, Market Cap, Sales, %Revenue, Relationship value, Account As Type, %Cost, Source and As of Date.)

4) Keep finding out each filtered firms' supply chain information, by identifying the supply chain table of the previous firm's supplier and add their data elements (a-f) into the database after using the same sub-industry restriction principle followed in the previous step.
5) Repeat step 4) until no more firms were discovered.
6) Check any overlapping data and delete them.

Industries	Count of firms
AEROSPACE & DEFENSE	52
ALUMINUM	8
AUTO PARTS & EQUIPMENT	3
ELECTRICAL COMPONENTS & EQUIPMENT	8
ELECTRONIC COMPONENTS	2
ELECTRONIC EQUIPMENT & INSTRUMENTS	11
STEEL	5
TIRES & RUBBER	2
Grand Total	**91**

Table 3-1Different Industries supplying Airbus- Tier 1

Secondary checks on data were made during March 2014. There are 4 tiers in the network. No further tiers were investigated as the fourth tier was composed of raw material suppliers upon inspection, which meant that the production process started from the fourth tier on average (see Section 4). : Tier 1 firms supply Airbus directly; the firms in Tier 2 directly supply Tier 1but not supply Airbus; Tier 3 firms supply Tier 2 firms directly but not supply either Tier 1 or Airbus; Tier 4 firms supply Tier 3 directly but not Airbus or Tier 1 or Tier 2. Figure 3-3 shows the hierarchy structure of different tiers relationship in the network according to the theory of shortest path to Airbus.

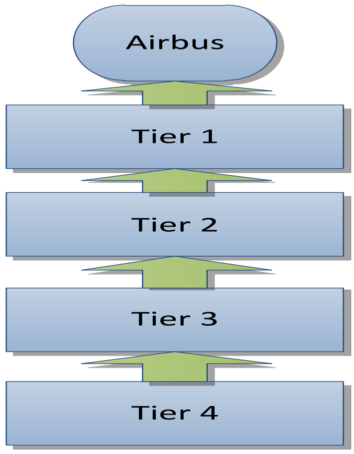

Figure 3-1Hierarchical structure of Tiers

3.2 Data validation

The sole source of data being the Bloomberg database needs to be challenged. Therefore, in an effort to validate these data the first action is cross checking with other database such as Marklines, OneSource and Factiva. It was found that the aerospace supply chain relevant information is very little in these databases. Due to the limit of data resource, the list of first tier suppliers, as the sample of database, is then validated by cross-checking with its official publication and internet resource.

51 suppliers were found in official publications;

Of these, 33 suppliers were found tohave supply relationships with Airbus

7 suppliers were not found to have cooperation with Airbus.

Therefore, 92.3% of first tier suppliers are verified thought official online information.

A secondary check undertaken by researchers on the annual report of the focal firm has shown that 90% of the firms listed on the Bloomberg database match the procurement relationships declared by the company.

3.3 Limitation and advantages of the data

There are a few limitations and advantages of the data that need to be highlighted, as they determine the type of analysis that is possible.

The first one is the data resource where the data can only be derived from an intermediary firm, i.e. Bloomberg, therefore the correction and reliability of data cannot be guaranteed first hand. However the supply chain data in Bloomberg is updated frequently, therefore the data can be corrected by dynamic data flow to improve the punctuality of the database.

Secondly, the links in the network signify that there is a supply relationship between the two nodes (i.e. firms), hence links are directional. Weights on links represent relationship magnitude, which is proxy by the percentage of revenue a buyer represents for a supplier firm. For example a 10 % weight on a directional link from a supplier to a buyer signifies that the supplier obtains 10% of its total annual revenue from that buyer. However, specific products which are supplied to which specific buying firm are unknown.

Finally, data is not exhaustive because the Bloomberg database contains only publicly listed firms. Another hindrance is that US regulations state that suppliers should be disclosed by listed firms, if their business accounts for more than 10% of the purchase. This means that relationships o companies within the US worth less than 10% may not be disclosed. However, several private companies are missing from the dataset. Despite this shortcoming the dataset is the most comprehensive dataset drawn to date on aerospace supply networks, and analysis shows statistically significant patterns can be identified, yet conclusions should be taken as suggestive rather than definitive given the lack of private firms and lack of knowledge on what proportion of the network is composed of them.

3.4 Social network metrics

The metrics can lead to identify the key firms and investigate network robustness, since social network metrics represent different embodiment patterns. The equations of relevant metrics used are as follows:

Degree centrality

Degree centrality is a simple centrality measure that can illustrate how many connections one firm has to others. In directed networks, each node has In-degree and Out-degree (Newman, 2010). So the degree centrality k_i of the node i in a non-direction network is:

$$k_i = C_D(i) = \sum_{j}^{N} x_{ij} \tag{3-1}$$

Where x_{ij} is the binary variable equal to 1 if there is a link between n_i and n_j and equal 0 otherwise. And in the direction network the links between supplier and customers can be distinguished (Kim et al., 2011). The In-degree centrality means how many suppliers the firm has and the Out-degree centrality is the number of direct customers. The metrics can help understand the directionality when considering positioning in the supply network. Formally these are defined as:

$$k_i^{out} = C_D^{out}(i) = \sum_j x_{ij}, \qquad k_i^{in} = C_D^{in}(i) = \sum_j x_{ji} \tag{3-2}$$

where X_{ij} is equal to 1 if there is an outgoing link between $n_i$and $n_j$and equal to 0 otherwise; and X_{ji} is equal to 1 if there is an incoming link from n_j to $n_i$and equal to 0 otherwise .

Closeness centrality

Closeness centrality measures the mean distance from a node to other nodes (Newman, 2010). The metric is frequently used in identifying which node can reach to others faster and consequently relates to a node's power and influence in the network (Freeman 1979, Brintrup et al. , 2013). Then the overall mean geodesic distance or shortest path from n_i and n_j in the network, is

$$l_i = \frac{1}{n}\sum_j d_{ij} \tag{3-3}$$

Commonly the inverse of l_i is called the closeness centrality C_i:

$$C_i = \frac{1}{l_i} = \frac{n}{\sum_j d_{ij}} \tag{3-4}$$

Betweenness centrality

Betweenness centrality is a different perception of centrality which calculates the extent to which a node lies on paths between other nodes. Nodes with high value may have significant influence within a network virtue of their control over information passing between each other. The nodes with highest betweenness not only derive a lot of power form the position within the network but also are the ones whose removal from the network will most disrupt communications between other nodes. Mathematically, let n_{st}^{i} be 1 if node i lies on the geodesic path from s to t and 0 if it does not. betweenness centrality$\mathrm{x_i}$ is given by,

$$x_i = \sum_{st} n_{st}^{i} \tag{3-5}$$

3.5 Weighted networks analysis

Airbus supply network is a weighted network. High structural heterogeneity is detected in the real social networks caused by of various capacity and intensity of relationships (Barrat et al., 2004).Binary links, which is either present or absent, are not enough to examine how relationships influence the network. The empirical data of Airbus supply chain also demonstrates that there is specific information relating to the strength and weight of each chain.

The quantity of percentage “revenue” is the proportion of revenue obtained from a particular customer. This value can be an appropriate parameter characterizing the weighed network. The suppliers will very rely on the customer more when the “revenue” is higher; in that case the customers have more power with higher weights in the network. Note that, the nominal “Relationship value” R_{ij}, which is the interaction value between the two firms, could not be considered as a factor of strength because a raw term like this will be misleading due to its large disparity: the range is from 1,300 dollars to 335 billion dollars. Here R_{ij} is defined as the weight value between firm i(customer) and firm j(supplier), The properties of the weighted network could be calculated by extending the definition of degree and combining it with the R_{ij} obtained from the empirical database. Where the degree is defined as,

$$k_i = C_D(i) = \sum_{j}^{N} x_{ij} \quad \textbf{(3-6)}$$

The strength of node can be expressed by the sum of its adjacency matrix strength, just as:

$$s_i = C_D^w(i) = \sum_{j}^{N} R_{ij} \quad \textbf{(3-7)}$$

Where R_{ij} should be greater than 0 if there is a link between node $i$and j. Comparing with non-weighted network the difference is the value in weighted network can be any number obtained, but not only 1 or 0.

To indicate the relative significance of number of links compared with the weights, the use of tuning parameter α is necessary to combine to strength and degree (Tore Opsahl, etc., 2010). Therefore, the weighted degree is defined as:

$$w_i = C_D^{w\alpha}(i) = k_i \times \left(\frac{s_i}{k_i}\right)^{\alpha} = k_i^{1-\alpha} \times s_i^{\alpha} \quad \textbf{(3-8)}$$

Where α is normally being set from 0 to 1:

1. ifα is 0 then the value will equal to the node degree;
2. ifα is 0.5 then the value is $k_i \times s_i$ which shows both number of ties and weight affect the value positively;
3. If α is one then the value will equal s_i, which means only weight effects.
4. In that case, It can be summarized as:

$$w_i = C_D^{w\alpha}(i) = k_i \times \left(\frac{s_i}{k_i}\right)^{\alpha} = k_i^{1-\alpha} \times s_i^{\alpha} = f(x) \quad \textbf{(3-9)}$$

$$= \begin{cases} k_i, & \alpha = 0 \\ (k_i \times s_i)^{0.5}, & \alpha = 0.5 \\ s_i, & \alpha = 1 \end{cases}$$

The Airbus supply network is a directional network due to the explicit directivity of interactions flow between the suppliers and customers. The s_i^{out} represents thus the sum of revenue node i supplied as a supplier, while the s_i^{in} represents the sum of revenue node $i$receives as a customer, then the In-weight and Out-weight are:

$$w_i^{in} = C_{D-in}^{w\alpha}(i) = k_i^{in} \times \left(\frac{s_i^{in}}{k_i^{in}}\right)^{\alpha} = \left(k_i^{in}\right)^{1-\alpha} \times \left(s_i^{in}\right)^{\alpha} \tag{3-10}$$

$$w_i^{out} = C_{D-out}^{w\alpha}(i) = k_i^{out} \times \left(\frac{s_i^{out}}{k_i^{out}}\right)^{\alpha} = (k_i^{out})^{1-\alpha} \times (s_i^{out})^{\alpha} \tag{3-11}$$

It is suggested to use value of α no less than 0.5 to analyse the properties of the weighted network and evaluate the different results while using different values of α.

To understand structural properties of the network more succinctly, we shall analyse the network with both weighted and non-weighted formations.

3.6 Robustness analysis

Robustness is a significant property of supply chain construction, which exposes how fast the network is broken down. The analysis of robustness can help us find the weaknesses in order to optimize supply chain management.

In this thesis the connectivity of network is the major performance of robustness in terms of the structural context of the data which only contains the firms and the transactions between these firms and does not involve any production attributes such as inventory, capacity, manufacturing rates and so on. In an effort to indicate the features of Airbus supply network robustness, the author simulates the network being attacked by removing a node or an edge continuously in the network. Of course, the term attack is used as a procedural term here. The failures of firms and links in the network to deliver goods could be due to several reasons including stoppages, disasters, logistics failures, collaboration cancellation or even terrorist attacks. The term of “attack” here describes the simulation procedure, and does not confine the analysis to actual “attacks”. When a node is removed, its links are also removed from the network.

Monitoring the behaviour of the network under attacks is done by observing the “largest connected component (LCC)”, and gives the network condition after such attacks. A component is composed of nodes that are directly or indirectly connected to each other. The largest connected component contains the highest number of nodes that are connected to each other. The extent of connectivity of network can be measured, through observing the size of the “largest connected component (LCC).

Nodes failures will be introduced to non-weighted network, while the link failures will be applied to weighted network. In the non-weighted network the links are either present or absent and links cannot be differentiated form each other; but in weighted network links bear different values of strength, and using this feature one can run weak or strong link failures to detect how relationship strengths effect the connectivity and community qualities in the network. On the other side, due to the various nodes’ parameters, such as in-degree, out-degree and betweenness centrality; diverse nodes failure scenarios can be operated in non-weighted network.

There are four node attack strategies in **non-weighted** network:

1) Random attack (A^{ran}): remove a node random from network G and its linked edges. Repeat the attack k_a times.
2) High-in-degree attack (A^{d}): remove the highest in-degree node from network G and its connected edges. Repeat the attack k_a times.
3) High-out-degree attack (A^{d}): remove the highest out-degree node from network G and its connected edges. Repeat the attack k_a times.
4) High-betweenness attack (A^{bet}): remove the highest betweenness degree node from network G and its connected edges. Repeat the attack k_a times.

The high-in-degree and high-out-degree and betweenness centrality of nodes in the network should be recalculated since the previous attacks finished, so that the next round attack can find the right target node

In **weighted network**, the edge failure has two scenarios:

1) Strong link attack (A^S): remove an edge with highest value of strength from the network, and repeat k_a times.
2) Strong link attack (A^w): remove an edge with lowest value of strength from the network, and repeat k_a times.

3.7 Tools and software

To model the Airbus supply network and calculate the metrics, Gephi* and NodeXL[2] are used.

NodeXL is an open-source template for Microsoft® Excel® 2007, 2010 and 2013 that makes it easy to explore network graphs. The software contains a number of networks analytic methods, for example centrality measures, group nodes analysis and sub-graph generation.

Gephi[3] is a collaborative imagining and exploration platform which is suitable for and complex networks, dynamic and hierarchical graphs. Gephi can detect the communities due to the metrics or their special organizations.

MS Excel[4]is used to store the database and analyse data and output from the software tools.

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[2]*Gephi.org © All Rights Reserved 2008-2014
[3]*NodeXL © 2006-2014 Microsoft
[4]*Excel © 2014 Microsoft Corporation. All rights reserved

4 Results and discussion

4.1 Overview of Airbus supply network

The overview of Airbus supply network map is created by the NodeXL using the empirical database (see Figure 4-1). 544 nodes and 1657 edges constitute the supply network in which Airbus is the centre surrounded by other firms; the different colours denote the different centrality degree they own.

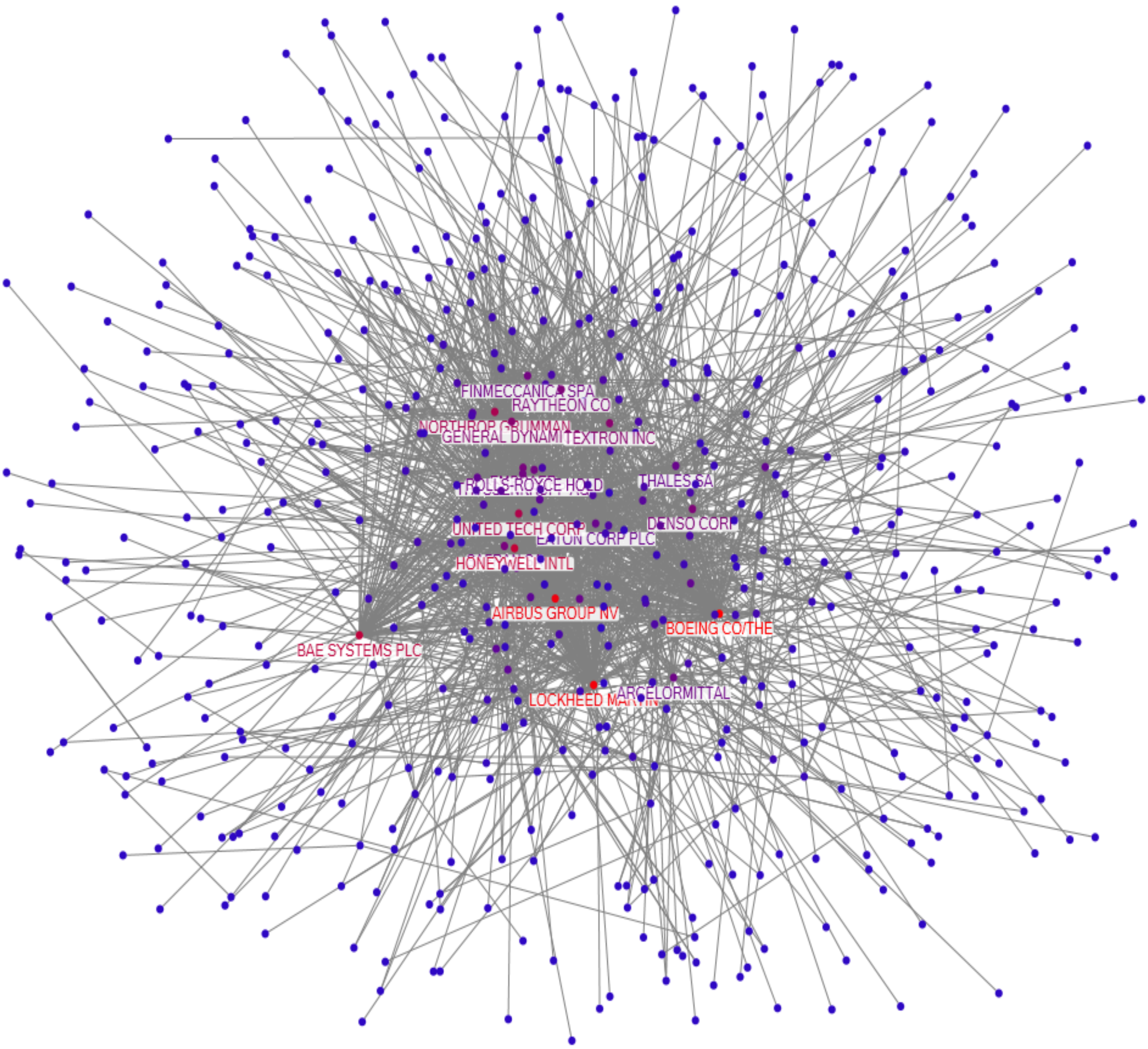


Figure 4-1 Map of AIRBUS supply network Highly central firms are entitled. (based on what centrality measure?)

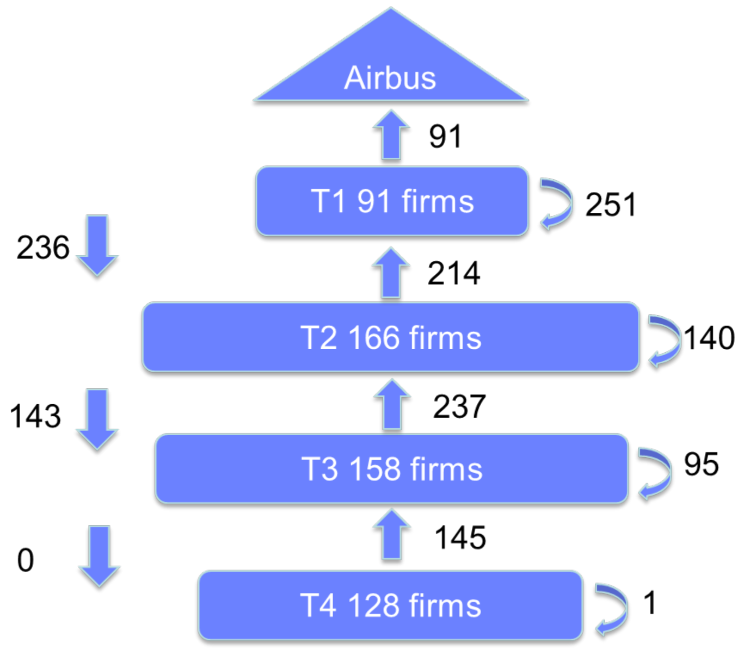
4.1.1 The hierarchy structure

Basic topology of the network with its tier construction is the beginning of network analysis from the overview perspective. In the field of supply chain management "tiers" are used to refer to the number of firms that lay between any given firm in the chain, and a final destination firm where goods end up. A firm that has a direct relationship with the final firm is considered a Tier 1. Any firm that supplies to this firm is a Tier 2, and so on. Tier levels serve as a proxy of the importance of a firm to the final firm, although research has shown that sub-tiers are just as important as close tiers during disruptions.

Tier 1 firms would be the closest allies of the final firm, coordinating upstream activities below. The length of the chain also affects the dynamics of the chain. For example, the longer the chain is, the higher the impact with which final tiers feel the demand amplification effect and the lower the reliability of the chain. Most companies do not have visibility over their chains: they only deal with their direct customers and suppliers, and do not have any power over their relationship choices, nor would they want to have – if they do, that means they are legally responsible for their actions. Furthermore, the chain is a dynamic construct, changing frequently, some efforts to map them, such as the study will only represent a cross-sectional reality in time. Given the emergent nature of supply chains, some abstract constructs have taken hold in literature, which have been seldom challenged.

One of these is the classical "pyramid" shape that puts forward the idea of hierarchical supply chains, in which a company only interacts with its upstream suppliers. These suppliers in turn repeat the same interaction pattern, resulting in a clear hierarchy, ensuring that the span of control for each firm is reasonably manageable. The pyramid abstraction has been used to highlight dependencies that cause all firms in the chain to ultimately work for the final, omnipresent assembler, whom everyone depends on for their survival (Cusumano and Takeishi 1991, Clark and Fujimoto 1991). The pyramid has been prevalent in literature that studies the automotive industry, particularly Toyota, to explain the dynamics of Keiretsu structures.

Figure 4-2 shows hierarchy structure of Airbus supply, in which the length of each tier represents the amount of firms in each tier. The overall structure looks like a barrel, for the top and the bottom are narrower than the middle tier; so the structure is not the model of pyramid assumed, the relationships in tiers also proved. Counting tiers is not obvious when investigate relationships between and within tiers. For example a firm that supplies directly to Airbus would be considered a Tier 1 supplier. If it supplies to another Tier 1 supplier of Airbus, the firm would also be a Tier 2, creating a triadic relationship between airbus, itself and the other Tier 1. It is found that a non-negligible portion of firms in the dataset exist on such multiple tiers (Figure 4-2). 72.5% of Tier 1 suppliers supply to other Tier 1 suppliers, 84.6% of firms is concurrently Tier 2 and 3. Hence, representing the supply network as a simple hierarchy is misleading. There are inter-tier supply relationships, cross-tier relationships and even



reverse tier relationships. The fuzziness of tier definition contrasts with previous studies largely based on the assumption of clear hierarchies and confounds the idea of straightforward linear control in the chain. For simplicity, classical definition of tier levels is rather than multiple tier membership in the rest of dissertation.

Since assigning suppliers to tiers is not as unambiguous as is typically assumed in the literature, it is possible to think of a firm's tier position in terms of various routes it reaches to the final customer. The metric "average path length" in network science calculates average numbers of nodes between firms. The average shortest path length between suppliers and any other firm within the network is 3.61. The supply network appears to be a tightly knit community, which means that – in principle – many firms have access to many resources. Rather than the unitary pathways that would define a strictly hierarchical network, a firm may have many dozens of potential routes whereby its output can reach the final customer. This feature suggests a network that would have significant resilience to disruption, but to understand how this works requires further examination of the pattern of links. The tier structure is not strictly linear, which can exaggerate things like bullwhip effects.

One possible explanation of this high degree of interconnectedness would be that firms generally have high numbers of customers and suppliers. However, the average number of customers per supplier is only 3.05 while the average number of suppliers is only 7.71, both quite small numbers. For a more thorough investigation of network structure it is needed need to study the network degree distribution.

It is surprising that both Boeing and Lockheed Martin appear in the second tier of Airbus supply network. The competition in commercial aircraft manufacturing between Airbus and Boeing is well known, but they are so close in the supply network and sharing the parallel aerospace industry resources. The subjective may thus extend to structure of aerospace. Airbus supply base is tightly connected to US and Boeing. They share many suppliers, which makes suppliers powerful.

4.1.2 Network degree distribution

The distribution of the number of relationships across firms in the network (degree distribution) demonstrates that the number of relationships maintained by firms in the supply network is not characterized by some random value, such as the Poisson distribution that it is expected for a random network (Erdos and

Renyi 1959) (see Figure 4-3 and Figure 4-4). Random networks are very rare in real-life, however they provide a useful model for comparison. The degree distribution of network approximates power-law behaviour, infers a scale-free network (Barabási and Albert, 1999). A scale-free structure would imply that a major amount of all dealings are linked with firms that act as hubs. In scale-free networks the degree distribution follows a power law, and hence corresponds to a straight line on a log-log plot. The results can neither refute nor reinforce the scale-free structure hypothesis as the scale of data is not high enough. What is certain though, is that the network carries a hub structure as in the Toyota study, and some firms connect to a significantly larger proportion of the network while most other firm connect to thee hubs only(Kim et al., 2011). Large firms are the connectors of the network. An implication of such a structure for network robustness is that the network will remain connected in the face of random disruptions, as these will most likely affect those firms that connect to large hubs. If, on the other hand, large hub firms are disrupted, the overall network will most likely suffer, given that they are integral to the functioning of the network(Barabási and Albert, 1999). Of course, this is a structural consideration only, and in reality a multitude of other variables such as inventory, and recovery efforts need to be taken into account. These consumption and implication will be proved through a network failure as follows.

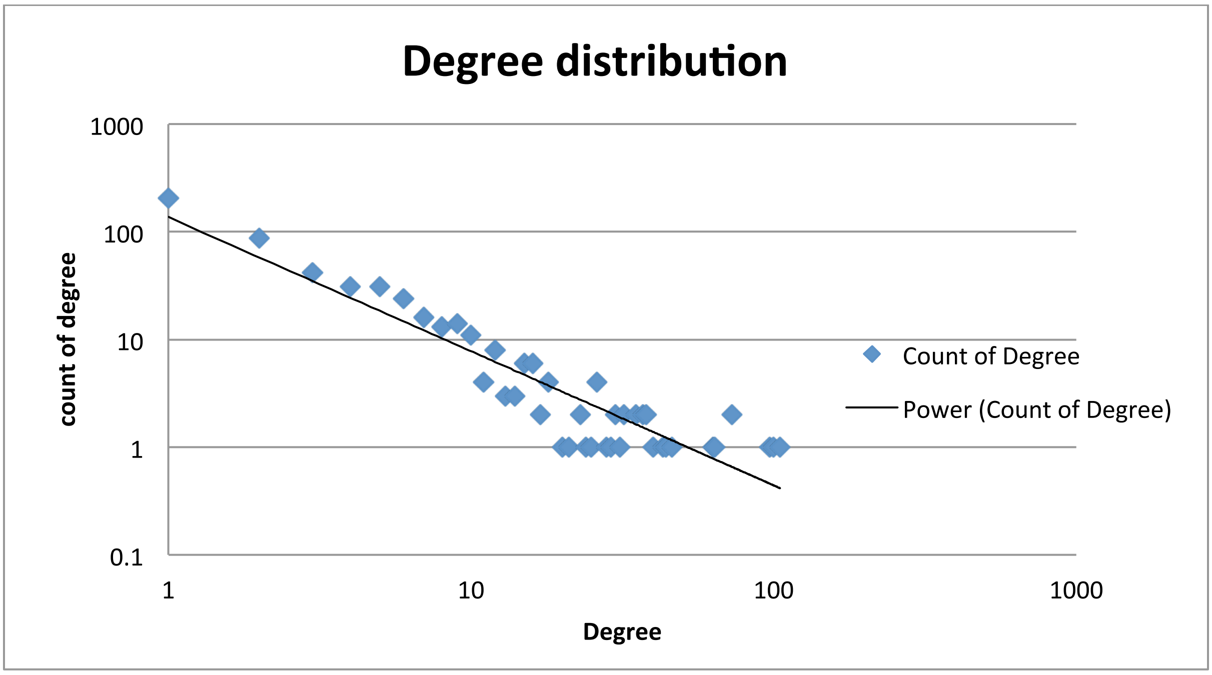


Figure 4-3Degree distribution

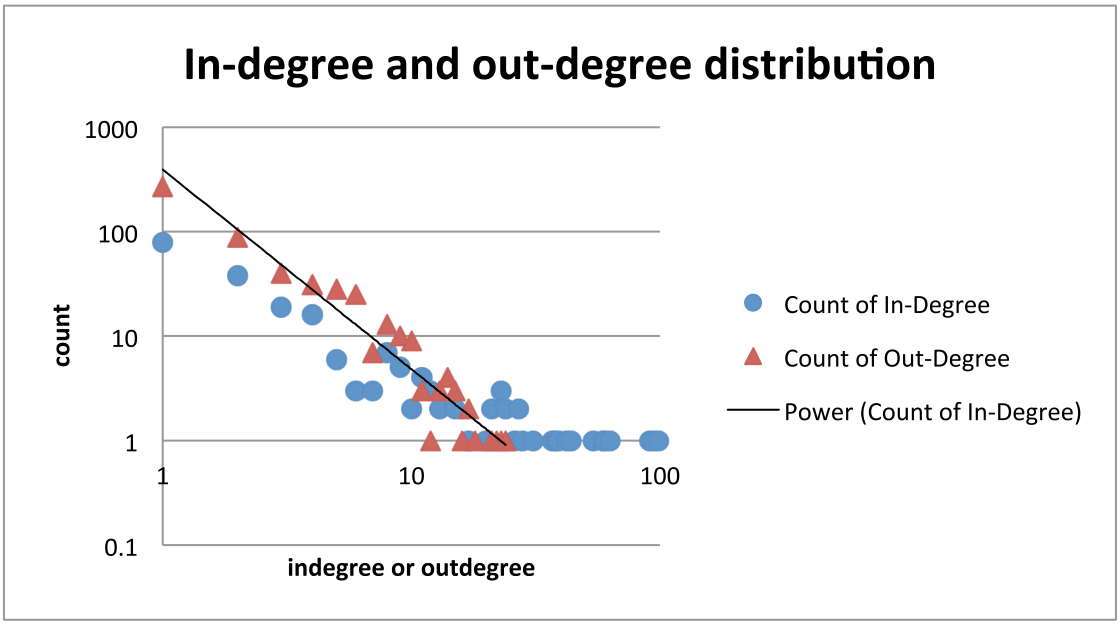


Figure 4-4 In-degree and Out-degree Distribution

4.1.3 Robustness of network

For revealing the properties of robustness of network, different attack strategies are applied to network as described in Section 5.

In this network, the attack strategies are:

A^{ran}	Random attack	A^{in}	High In-degree attack
A^{out}	High Out-degree attack	A^{bet}	High Betweenness attack

The in and out degrees of all nodes are calculated. Starting from the node with the highest in or out degree or betweenness, nodes are removed successively in descending order of node degree. After a node is removed, the topology of network has changed. Hence with the purpose of find the next right firm with highest degree, the parameter of each node should be recalculated after each attack.

In this case of random failures, a random node is removed from the network and the random failure is repeated 30 times in order to obtain relevant confidence intervals. In this case, the simulation will start off with a completely connected network; hence the size of the LCC is 1. The size of the LCC in each round is normalized by dividing by the size of the largest connected component in the original network.

In this failure simulation, there are 50 rounds attack to remove 100 firms in the network, in other word 2 firms has been removed in each attack round.

For example, number of attack trial as n, then the procedure in betweenness attack strategy is below:

1) Step 1: to calculate the betweenness centrality of each node in the network
2) Step 2: to remove the two nodes with the first two highest betweenness centrality
3) Step 3: to measure fraction size the largest connected component LCC-new in the new networks in which there are (N-2n) nodes
4) Step 4: to transfer the LCC-new to the LCC-original, for the network size has changed by removing the nodes. The LCC-original = (LCC-new)*(N-2n)/544
5) Step 5: repeat the step 1- step 4 until n=50.

Record LCC in each round, then the figure of LCC falling can be drawn.

The changes of the size of the LCC show under different failure type in Figure 4-5. The network rapidly disconnects when firms with large numbers of suppliers stop functioning, whereas connectivity is more stable and sustained under more numbers of random failures. The pattern is similar when firms with large numbers of customers are targeted, signifying that suppliers with relatively high numbers of suppliers themselves are integral to connectivity. Of course it should be noted that in the Airbus network, firms have large numbers of suppliers, but small numbers of customers, because the network under consideration does not contain customers outside the Airbus network. In other words, all customers of suppliers themselves are suppliers to the Airbus network. Nevertheless, counting the number of suppliers to suppliers appears to be a good proxy for estimating structural robustness. If define when the LCC is no more than 5%, the network will be fail. On average it takes 450 firms, which are most 83% of total firm number, to fail for the network to be disconnected under random failure, whereas the failures of hub firms disconnect the network immediately. The hub may associate with different groups or communities, thus with the aim of finding the communities construction, the different sector distributions will be analysed in next sub-section.

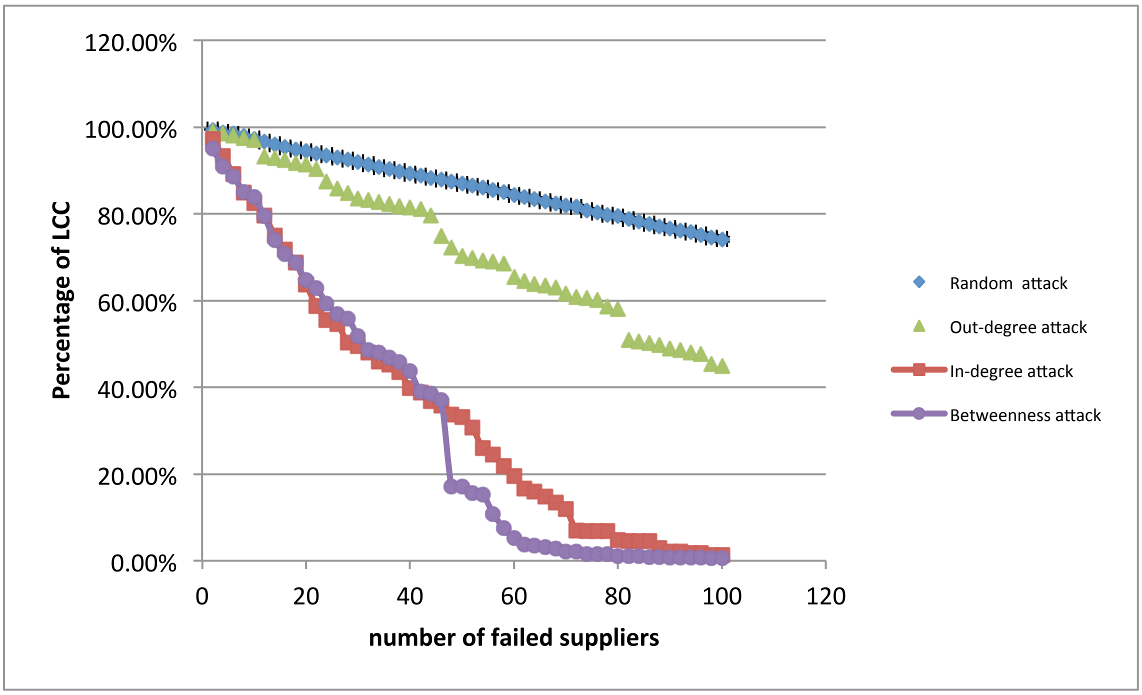


Figure 4-5 Changes of LCC in different attack strategies

4.1.4 Geography distribution and Sub-industry distribution

Figure 4-6 shows the geographical distribution of firms across tiers. The classification of different regions is shown in Table 4-1.Thirty-eight countries are involved in the supply network, the highest being from USA (25%), Japan (23%) and China (19%) respectively. It is interesting that the top three does not include a European country, however when taken together, European firms account for the majority of Tier 1 suppliers, followed by firms in USA. USA and Asia dominate Tier 2, and Japan dominates Tier 3. Asian countries dominate Tier 4. The network is global, and there appears to be clear geographic bias on the different levels of tiers. The significance of these values has been checked using a two-tailed hypergeometric test.

Considering the collected data from sector bias view, they can be defined themselves as one of Aerospace, Electronics, Automotive, or Raw Material producers. Tier 1 consists mostly of Aerospace suppliers, Tier 2 and 3 by Electronics followed closely by automotive suppliers according to investigation of their distribution across tiers (see Figure 4-7).

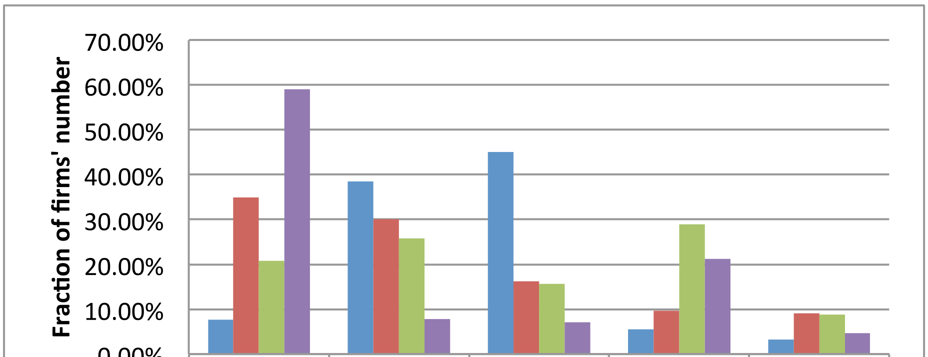
The amount of automotive suppliers in the network is surprising, and highlights how closely linked are the aerospace sector with the automotive industry. Companies like GKN and Mitsubishi Heavy Industries provide much of the interconnectivity as they produce both aerospace and automotive components. GKN produces airframes for Boeing and Airbus as well as drivelines for Toyota. During the Japanese earthquake in 2011, GKN’s shares fell rapidly as Production in Japan was severely impacted, but recovered later thanks to improved production and sales in other divisions including aerospace.

Raw materials suppliers are small in number, and do not dominate any one tier, although they increase as the tiers go down. There appears to be a relationship between a firm’s location and industrial sector identification, and its tier distance to the focal firm, Airbus. Final tier is raw materials but there seems to be only a few companies, creating vulnerability and competition

when resources are scarce.

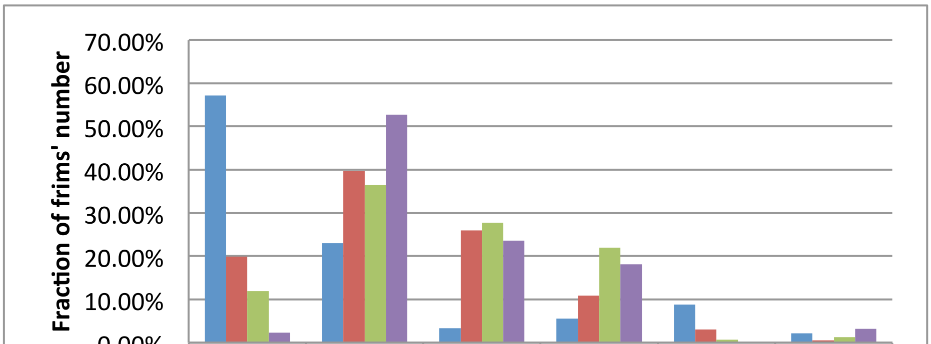
Asia	EURO		Others
CHINA	AUSTRIA	NETHERLANDS	AUSTRALIA
HONG KONG	BELGIUM	NORWAY	BRAZIL
INDIA	BULGARIA	POLAND	CANADA
INDONESIA	DENMARK	ROMANIA	MEXICO
ISRAEL	FINLAND	SPAIN	NEW ZEALAND
MALAYSIA	FRANCE	SWEDEN	RUSSIA
SINGAPORE	GERMANY	SWITZERLAND	SOUTH AFRICA
SOUTH KOREA	IRELAND	UNITED KINGDOM	TURKEY
TAIWAN	ITALY	LUXEMBOURG	UKRAINE
THAILAND			

Table4-1 classification of different regions



	Asia	US	EURO	JAPAN	others
tier 1	7.69%	38.46%	45.05%	5.49%	3.30%
tier 2	34.94%	30.12%	16.27%	9.64%	9.04%
tier 3	20.75%	25.79%	15.72%	28.93%	8.81%
tier 4	59.06%	7.87%	7.09%	21.26%	4.72%

Figure 4-7Geographic distribution of firms by tier



	AEROSPACE & DEFENSE	ELETRICAL AND ELECTRONIC	AUTO PARTS & EQUIPMENT	STEEL	ALUMINUM	TIRES & RUBBER
tier 1	57.14%	23.08%	3.30%	5.49%	8.79%	2.20%
tier 2	19.88%	39.76%	25.90%	10.84%	3.01%	0.60%
tier 3	11.95%	36.48%	27.67%	22.01%	0.63%	1.26%
tier 4	2.36%	52.76%	23.62%	18.11%	0.00%	3.15%

Figure 4-6Sector distribution of firms by tier

From the overview layout of geography distribution (see Figure 4-8), it is clear that the firms from US and Europe consistof the core of Airbus supply network. Furthermore, the firms of Japan look like a community beside the central community that is more independent, though the Asian firms are on the periphery of the network. The phenomenon also can be explained by the data in Figure 4-6.

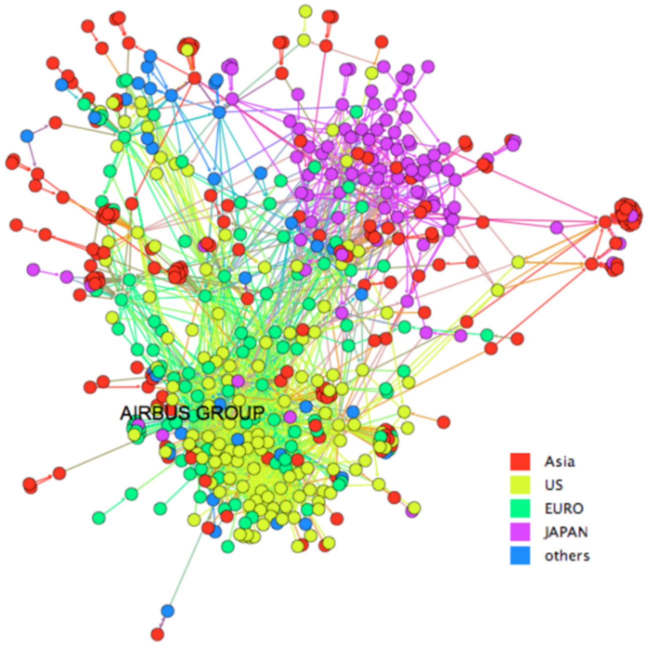


Figure 4-8Network visualization of suppliers from different regions

By comparing the European supply region and US region in terms of individual topologies of their network (see Figure 4-9), both the size and density of US graph is bigger than EURO region according to the data that there has 136 nodes and 409 edges in the US topology contrasting103 nodes and 182 edges in EURO. The comparison may indicate that the US region has more influence and more associative than EURO and others.

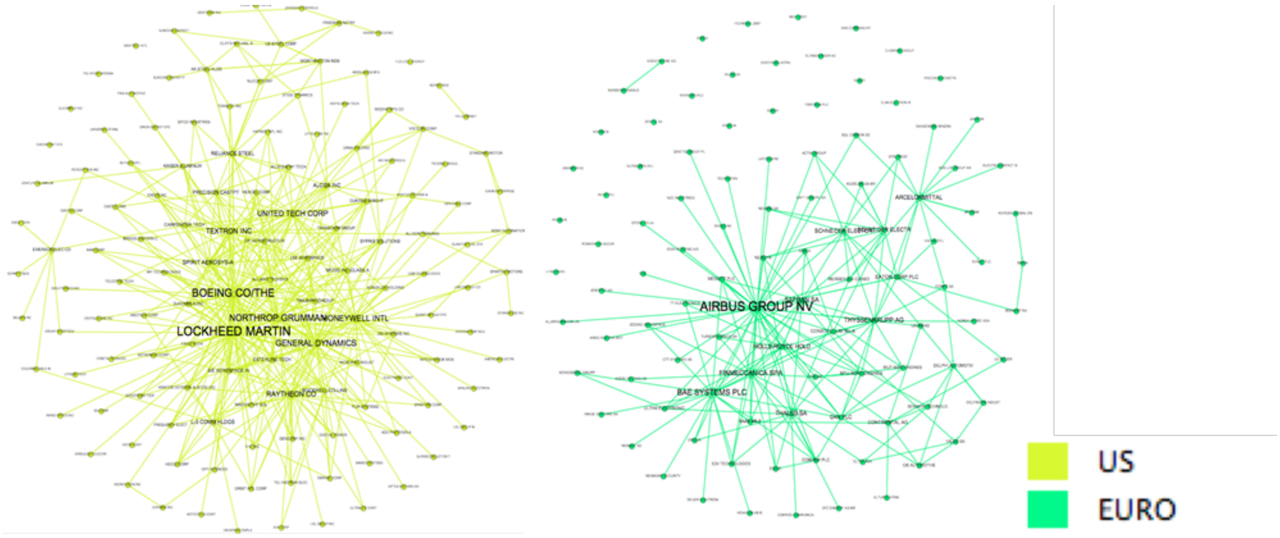


Figure 4-9Comparison of topologies between USA and EURO

From the overview of the sub-industry distribution (see Figure 4-10), there are three comparatively independent communities in the network: these are Aerospace & Defence, Automotive parts equipment and Steel. Comparing with them Electrical and Electronic seem like a cloud covering the whole network, less connection with each other though. Rubber and Aluminium suppliers are very few in number. For showing the features of communities more particularly and supporting the assumption, some other metrics of networks will be introduced to analyse the connectivity of sub-networks later.

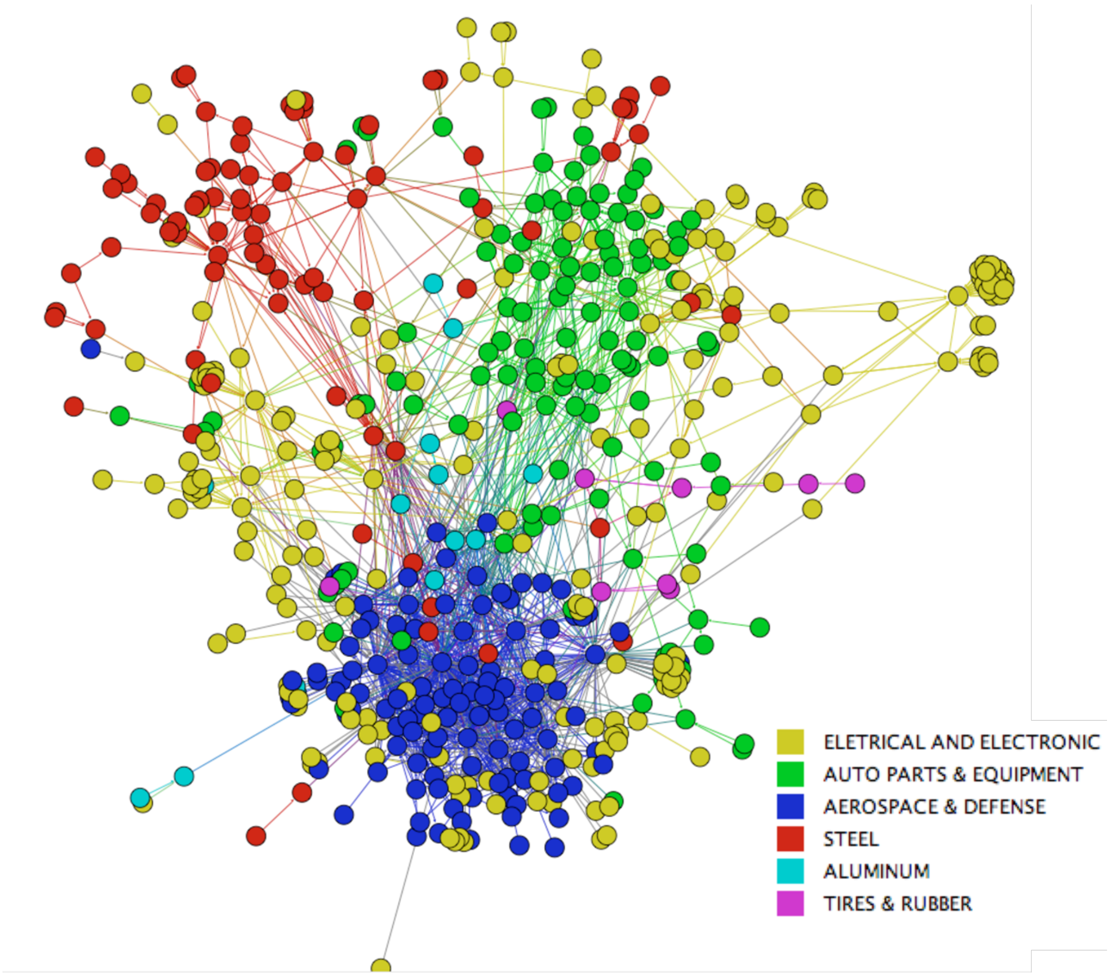


Figure 4-10Network visualization of suppliers from (b) industrial sectors

4.1.5 Connectivity

The density of a network is a simple measure of overall network cohesiveness, with high-density networks containing multiple paths between any two firms. Density is measured by calculating the number of links in a network as a fraction of the number of all possible links.

The random networks with the same size of Airbus were generated 30 times repeatedly so as to get the confidence intervals. To guarantee to get the size of the network using Gephi platform, the wring probability should be $p = 2 * E/N * (N-1)$, where E is 544 and N is 1657 (Gilbert, 1959).When compared with random network, the density of the network is only slightly lower than random networks; however the clustering coefficient is significantly higher. The aerospace industry is not tightly connected, as there are many more possible links, however, those firms which do show high degrees of connection appear to connect to each other via third parties as well. The implication is that the network on the whole does not have high cohesiveness but the network is divided into communities of firms that are intricately linked to one another. This also implies that a few firms act as the connectors between these communities, and their role is key to provide overall connectivity. Examination of those firms will be in section 4.3.

In addition, it is observed that density varies from Tier 1 to Tier 4, among different locations, and different industrial sectors (Table 4-1), hinting at the existing of sub-structures with different levels of cohesiveness. While the European, Japanese and North American firms connect within each of their sub-networks to a similar degree, Asian firms do not interconnect as much.

For further research, a formal test is applied to determine the existence of communities using the modularity measure. The measure essentially investigates the strength of division into sub-groups in a network. Biological and social networks show high modularity and form themselves into densely connected communities. Communities are important in understanding the dynamics of the network. For instance, a closely connected social community will imply a faster rate of transmission of information or rumour among them than a loosely connected community (Newman, 2006). In epidemiology the resistance of connections between communities determine the rate of transfer of diseases throughout the network of humans. Furthermore, communities give a new resolution in the network under study, as different communities may have different sub-structural properties. Formally, modularity is the fraction of the edges that fall within the given groups minus the expected such fraction if edges were distributed at random. The value of the modularity lies in the range [−0.5, 1). It is positive if the number of edges within groups exceeds the number expected by chance. For a given division of the network's vertices into some modules, modularity reflects the concentration of edges within modules compared with random distribution of links between all nodes regardless of modules. Although different methods of calculation have been proposed, the chosen one is the method described by Girvan and Newman (2002). Trial with different resolution factors is shown on Table 4-2. Modularity seems to be high in this network and close to that of networks reported in literature, including metabolic networks, collaboration networks of physicists, and jazz musicians (Newman, 2006).

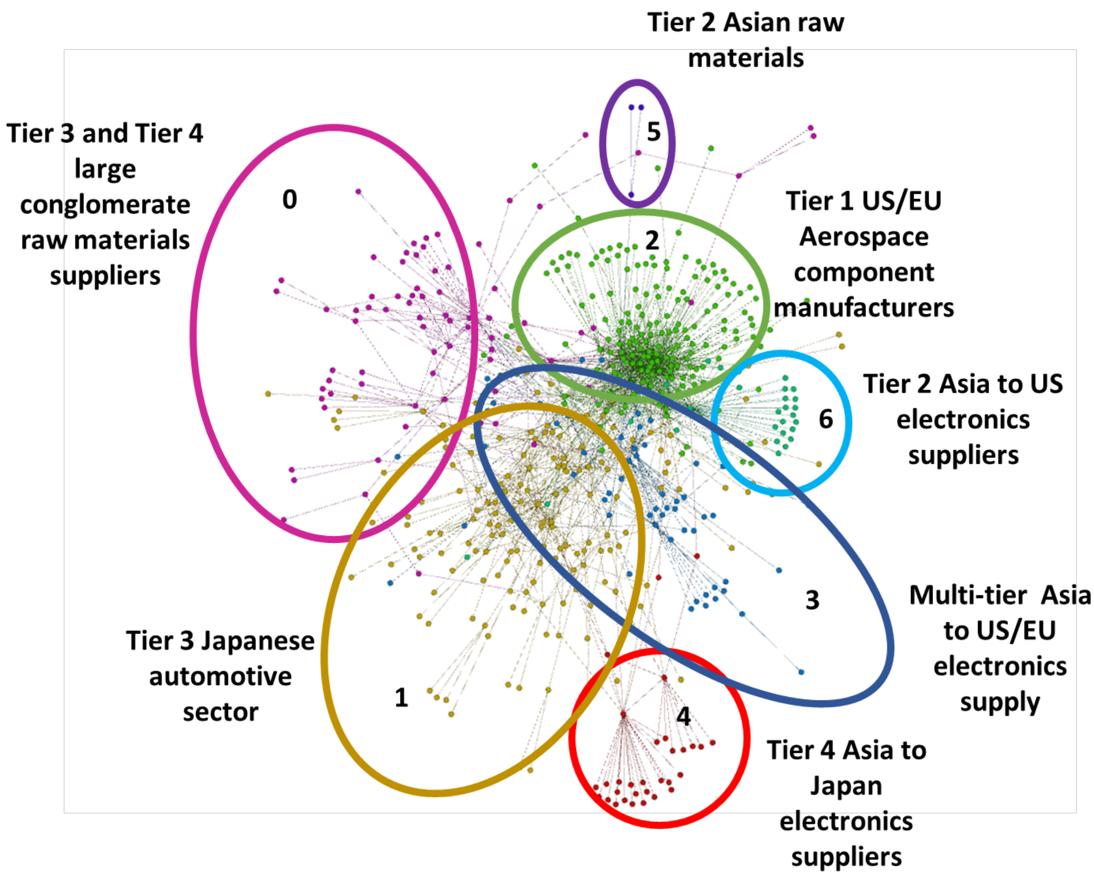
	Size	**Density (Undirected)**	**Clustering Coefficient**	**Average shortest path length**
Whole supply network	544	0.011	0.314	3.61
European sub-network	103	0.034	0.351	2.71
North American sub-network	136	0.043	0.441	2.71
Asian sub-network	173	0.004	0.081	2.01
Japanese sub-network	94	0.035	0.257	3.04
Random network	544	0.011 +/- 0.1e-8	0.011 +/- 0.002	3.68 +/- 0.016
Tier 1	91	0.06	0.388	2.44
Tier 2	166	0.01	0.388	4.187
Tier 3	159	0.007	0.1410	5.014
Tier 4	127	0	0	0

Table 4-1Structural measures of sub-networks

Resolution	**Number of communities**	**Modularity**
0.5	22	0.413
0.8	11	0.472
1	7	0.460
2	5	0.446
3	3	0.428

Table 4-2Modularity in different resolutions

Taking the resolution value of 1, there are 7 communities being found in the network detected by the algorithm given by Blondel et al (2008) and shown on Figure 4-11. Although the algorithm does not have any industrial intelligence embedded within it, it is able to find logical patterns solely based on topological data. Of the seven communities detected, first is a raw material exchange between US, Europe and Asian firms, in Tier 3. Second is the Japanese auto producers community composing of mostly Tier 3 firms. Third is the US Aerospace component manufacturers directly supplying to Airbus. Fourth are second tier Asian electronics manufacturers, while fifth and sixth are once more Asian electronic component manufacturers that make up fourth and second tier. The difference between fourth and sixth community is that the third community shares links with European auto and aerospace manufacturers directly. Finally a tier 2 community is observed that it is mostly an interchange between US and Asian Tier 2 electronics producers.



Community	Number of firms	US	EU	ASIA	OTHER	JAPAN	RAW	AERO	ELECTRONICS	AUTO	TIER1	TIER2	TIER3	TIER4
0	77	0.21	0.19	0.38	0.21	0.01	**0.74**	0.01	0.22	0.03	0.06	0.19	0.45	0.29
1	163	0.15	0.11	0.23	0.02	**0.48**	0.14	0.02	0.29	**0.54**	0.03	0.21	**0.45**	0.30
2	183	**0.41**	0.28	0.19	0.09	0.03	0.09	**0.54**	0.28	0.08	**0.39**	0.33	0.20	0.07
3	59	0.15	0.24	**0.56**	0.00	0.05	0.08	0.02	**0.76**	0.14	0.10	**0.49**	0.15	0.25
4	31	0.00	0.00	**0.87**	0.00	0.13	0.00	0.00	**1.00**	0.00	0.00	0.06	0.06	**0.87**
5	3	0.00	0.00	**1.00**	0.00	0.00	**0.67**	0.00	0.33	0.00	0.33	**0.67**	0.00	0.00
6	28	**0.39**	0.18	0.32	0.04	0.07	0.00	0.11	**0.64**	**0.25**	0.07	**0.82**	0.07	0.04

Figure 4-11Communities and their properties in the airbus network Using a hypergeometric test, significantly over-represented node attributes are in bold script.

4.2 Weighted network

In this network, the revenue details represent the strength the links among nodes, by which the relationships between topology and finance can be studied. With the weight of the link, the relation of supply and demand represents more clearly than the binary network, the key links and key firms are found more accurately.

In addition, due to the variety of links, removing them in order can reveal the roles of links. Thus in this section, comparison of weight, strength and degree distribution will be addressed first; and then the robustness properties of edges failures will be analysed followed. For demonstrating the combination of both features of number and strength of edge, tuning parameter α is set to 0.5, and the following results are all based on this value of α.

4.2.1 Weight distribution

The distributions of weighted In-degree and In-strength are similar to the In-degree distribution that is approximated by the power law shown in Figure 4-11. In addition, the Figure 4-12 also illustrates the weighted Out-degree and Out-strength follow the tendency of Out-degree power law distribution. It may be said that few firms hold majority of resources.

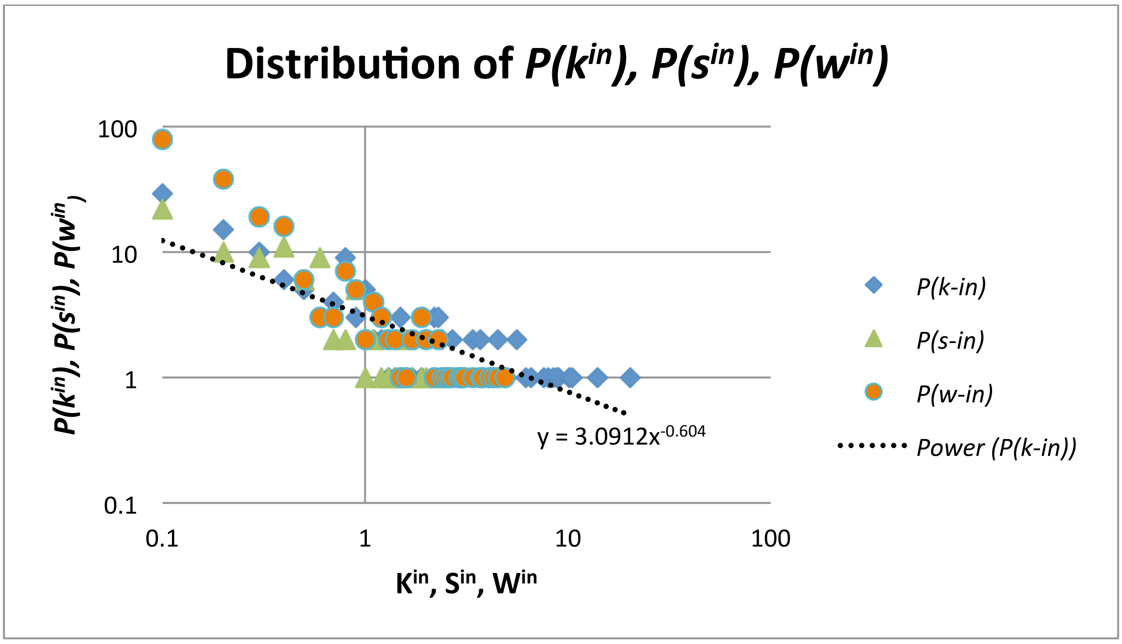


Figure 4-12 Distribution of *P* (*K^in*), *P* (*S^in*), *P* (*W^in*)

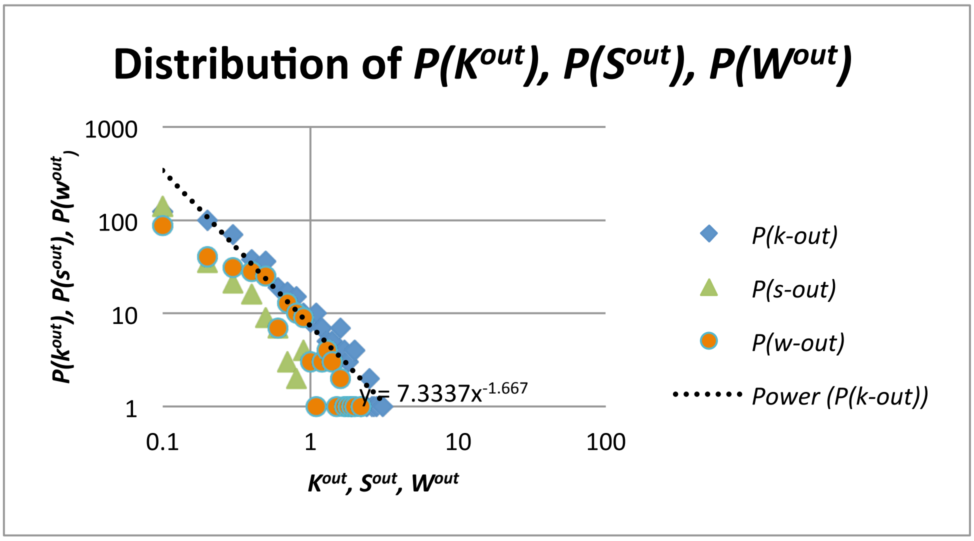


Figure 4-13 Distribution of *P*(*K^out*), *P*(*S^out*), *P*(*W^out*)

There is a correlation between weight and topology of network in terms of the average In-strength$\langle s^{in} \rangle$ and average In-weight $\langle w^{in} \rangle$ as functions of In-degree k^{in} in Figure 4-13, nevertheless, average Out-strength and Out-weight does not show the correlation very much. It may be observed that the firm with high in-degrees can hold more weigh rather than the firms with high Out-degrees.

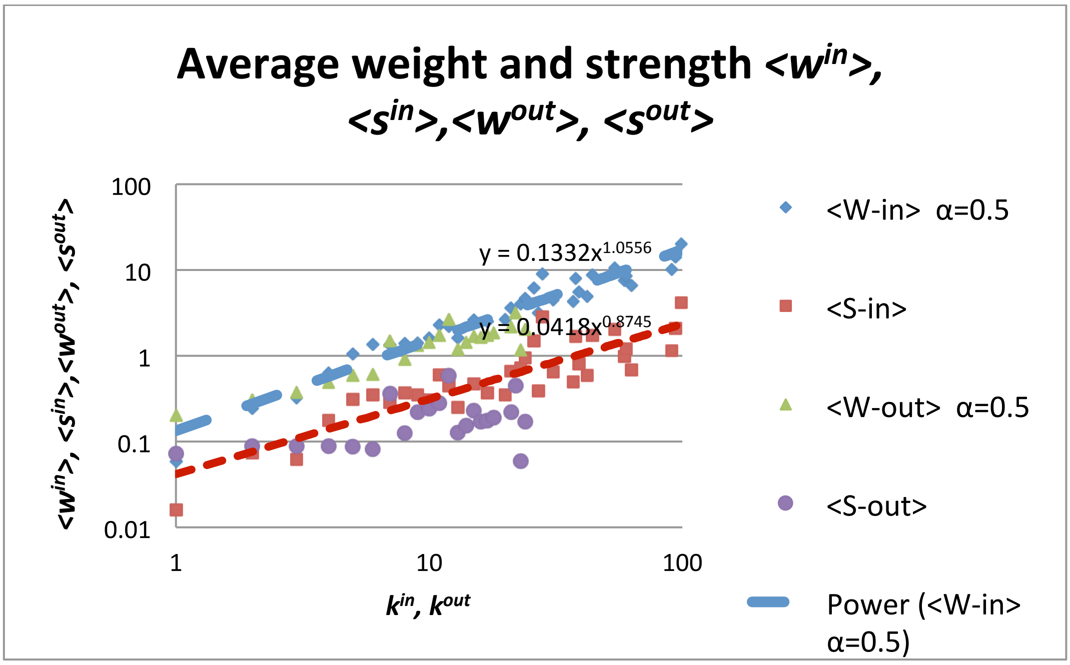


Figure 4-14 Average Strength and Weight of In-degree and Out-degree Distribution

From another perspective of Average total In-weight and Out-weight as functions of In-degree and Out-degree individually, a significant correlation between weight and topological features exists, that suggests that the larger is a firm with high degree, the more weight it can handle.

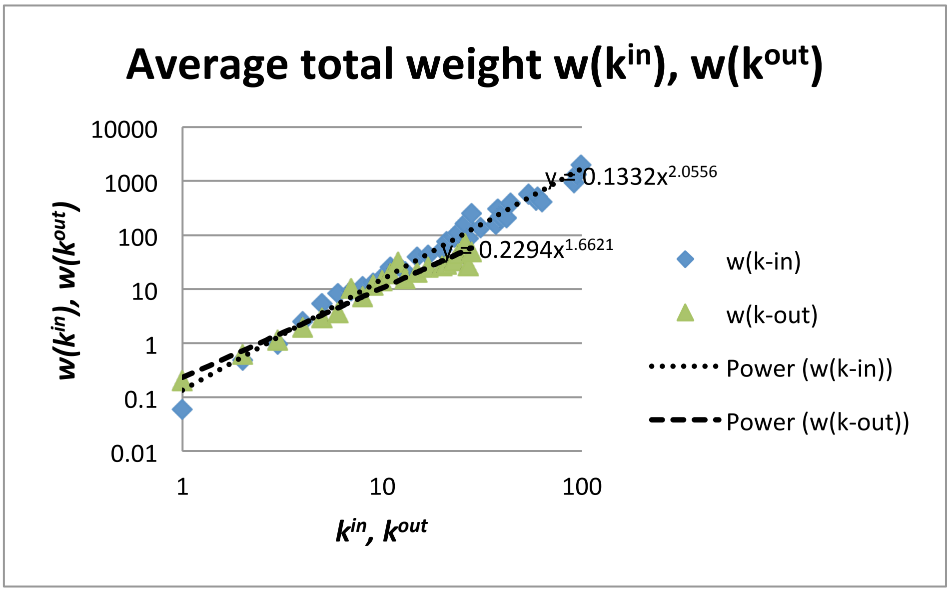


Figure 4-15Average total weight *w* (k^{in}), *w* (k^{out})

4.2.2 Robustness and communities of weighted network

As section 4.1 mentioned, there are communities in the network, but which kinds of links connect them together need to be explored. In social networks, strong and weak links are distributed separately. Strong links are held within communities while weak links connect them together. In this case, the network fails more quickly under weak link removal than the strong ones (Riitta et al., 2007). In our case, the edge with high value of strength is defined as strong link, while the low strength denotes weak link. To explore this phenomenon in our network, we deploy two link failure strategies:

A_E^S Strong link attack: to remove the edges with highest strength to edges with lowest strength repeatedly.

A_E^W Weak link attack: to remove the edges with lowest strength to edges with highest strength repeatedly.

The features of connectivity of network under two different strategies is shown in Figure 4-15,

According to the figure of weighted edge failure, the results are different from the literature. There is a cross point between the two descending curves; that indicates the strong link failures affect the network more than the weak ones, but after almost 80% edges failed the weak edges failure strategy makes the network drop suddenly even faster than the strong strategy. This makes sense in a supply network, because of its tier structure, products are produced within communities, and they come together when one community buys from another to assemble. Thus within communities, buyers and sellers may shift, and their links might be weak, but between communities there is usually a central firm that is tasked with integrating sub-parts and forwarding them to the other community. These firms seem to be powerful hubs, which remain as key actors in the network, acting as bridges. Thus their relationships with other communities are strong and relatively more stable.

Based on community structure theory of Tovionen etc., (2007),it may be said that in the real Airbus supply network:

1) There are some strongest links are embedded between different communities, that makes the size of LCC drop faster than weak link strategy.

Definitions: Due to the cross point appears after 75% links failed the both sizes of LCC drop at around 46% by two failure strategies. Therefore, I divided them into three stages. I define that the edges in stage 1 are strong links in strong strategy and weak links in weak strategy, there are the first 25% edge failures, while the edges in stage 3 are the other way around. The 50% edges in stage 2 are medium links.

2) The strong links are very impressive, no matter in the in stage 1 or stage 3 they make the network crush worse than the weak ones.
3) However, it can be seen the combination of weak and medium links reaches the same level of combination of strong and medium
4) Overall, the weak links strategy wins the competition of destroying the network completely.

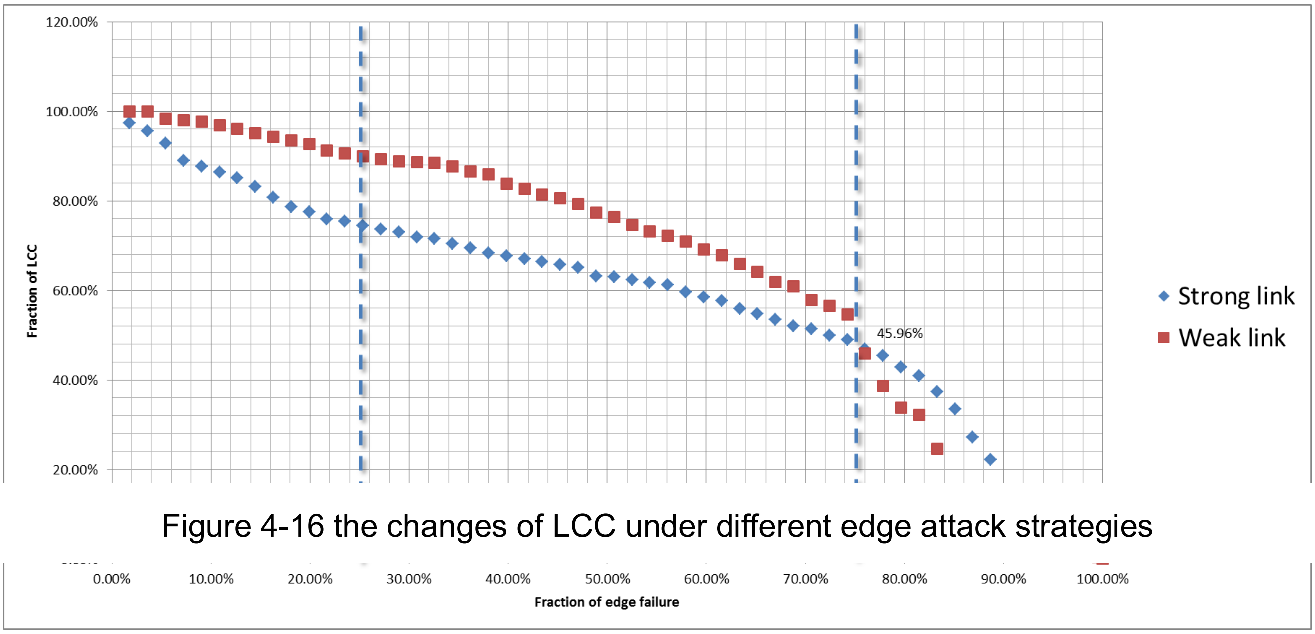


Figure 4-16 the changes of LCC under different edge attack strategies

4.3 The key firms

In the previous section it was shown that the overall structure of the network is composed of hubs, to which most firms are connected. The network is vulnerable to disruptions on these hub firms but resistant to random disruptions. Furthermore, the network is composed of several sub-communities, the membership of which is dictated by a firm's tier, geography, and industrial sector. Certain firms will connect these sub-communities, providing the glue that holds the network together. These firms will also act as bridges that transfer information and materials in the network. They seem to be holding strong links between communities that produce sub-parts in each industrial sector, which are then assembled through strong connections between communities. This section will identify these key actors by using network centrality measures and discuss how they impact the network. While network level measures such as average path lengths and density provide macroscopic views of how the overall structure is organized, centrality measures provide a node level view and examine how a certain node is embedded within a network.

Degree centrality is a well-known measure that simply counts how many connections a node has. Network scientists correlate Increasing degree of a node with increased influence and popularity. One of the theoretical dynamics that give rise to scale-free networks is what is known as preferential attachment, a system in which nodes attach to other nodes with a probability proportional to the number of connections a node has (Barabási and Albert, 1999). Hence high degree nodes are also more likely to attract new connections, increasing their size exponentially (2011). Kim and Choi (2011) relate the degree of a node in a supply network to "the extent with which a firm has an impact on operational decisions or strategic behaviour of other firms", and that degree central nodes should reconcile differences of members, and coordinate the network. In and out degree centrality represents the extent to which a node has incoming and outgoing connections respectively. Ni supply networks, these correspond to the number of suppliers and buyers a firm has. Nodes that have high in degree centrality will be integrators that assemble components that go into a final product and are integral to the architectural design of the product, whereas nodes with high out degree centrality are concerned with distributing limited resources among several customers (Kim et al., 2011).

Conceptualized by Freeman(1978–1979), betweenness centrality measures how often a node will sit on the paths that connect different nodes to each other in the network. Nodes with high betweenness centrality have been shown to control the flow of materials and communication in the network (Kim et al., 2011). Consequently they can control the speed with which information and material can be disseminated in the network and act as bottlenecks. It is important to point out that; betweenness centrality counts shortest paths, whereas all paths are in use in a supply network as firms work towards a bill of materials. A more refined measure should include all paths; however in this dissertation base the discussions on the conventional definition of this measure so that comparisons with previous empirical work can be made.

Finally, closeness centrality provides a measure of how close a firm is to other firms in the network by counting the total geodesic distance between a node and all other nodes in the network. Kim et al (2011)put forward the idea that firms with high closeness will benefit from short supply chains and suffer less from classical supply chain issues such as bullwhip effect; as well as gaining the ability to act independently, given its ability to access information in the network faster than other firms.

Figure 4-17 shows the distributions of out-degree, in-degree, closeness, and betweenness centrality measures. Following Kim et al.’s(2011)terminology, relate these measures to demand, supply, informational dependence, and operational criticality respectively.

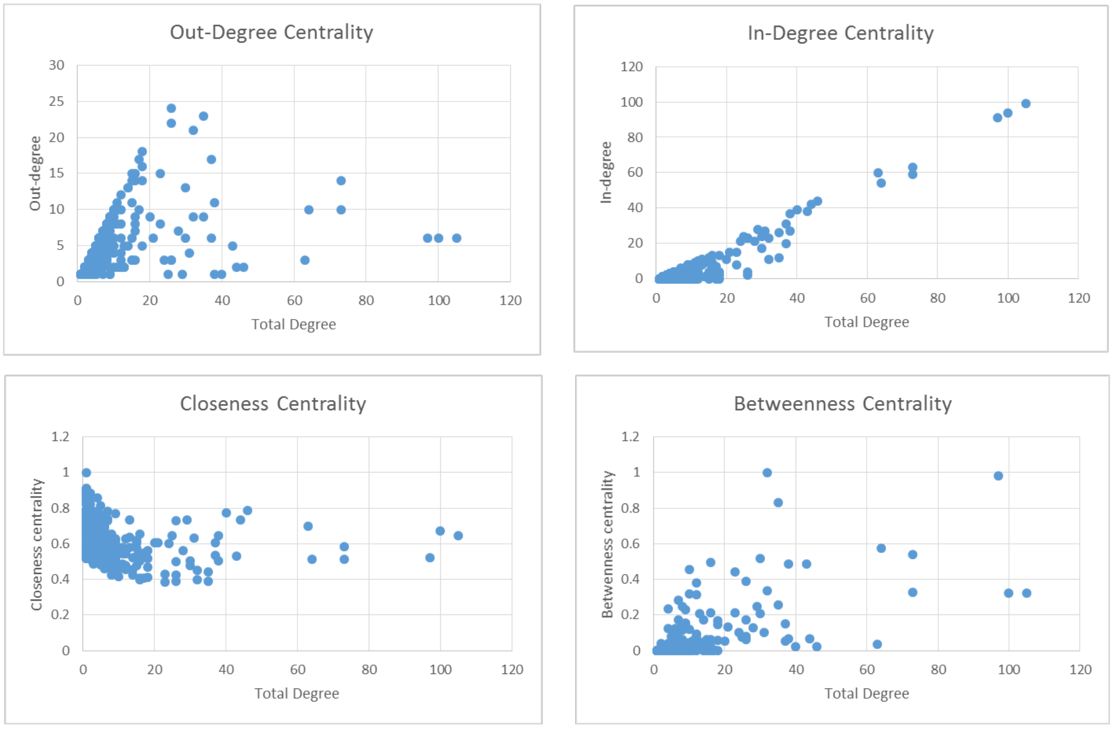


Figure 4-17Network centrality distributions

Out degree Demand Load	In degree Supply Load	Closeness Informational independence	Betweenness Operational Criticality
ALCOA INC (1)	BAE SYSTEMS PLC *(2)*	NHK SPRING CO *(2)*	EATON CORP PLC (1)
THYSSENKRUPP AG (1)	NORTHROP GRUMMAN *(2)*	***ALCOA INC (1)***	ARCELORMITTAL (2)
PRECISION CAST*(1)*	***HONEYWELL INTL (1)***	*THYSSENKRUPP AG (1)*	***UNITED TECH CORP (1)***
GKN PLC (1)	***UNITED TECH CORP (1)***	VALE SA-PF (2)	***HONEYWELL INTL(1)***
ESTERLINE TECH*(1)*	GENERAL DYNAMICS (3)	***GKN PLC (1)***	HITACHI LTD (2)

Table 4-3 Top five firms in each centrality measure

Firms that are repeated in different measures are bolded and italicized. Tiers are given in parentheses next to each firm.

Multiple firms score highly in multiple measures of centrality. Of these, both Alcoa Inc, Thyssenkrupp AG, and GKN PLC have a high demand load and informational independence. They seem to have many customers and at the same time, place themselves at a topologically close position to others in the network, forming short supply chains. Alcoa Inc is a producer of aero engine and structural parts such as airframes, and is the world's third largest producer of aluminum. Its products are used in both the automotive and the aerospace sector, which might explain its closeness as it sits between the aerospace and automotive communities. Thyssenkrupp AG is similar in the sense that it is one of the world's largest steel producers, and also supplies to both aerospace and automotive OEMs. GKN PLC produces components for both sectors too. Although it used to be a steel producer, it sold this part of its business, and focused on aerospace and automotive lately, after buying a Japanese driveline producer.

Two firms with high supply load also are operationally critical. These are Honeywell Inc and United Technologies Corp. They have many suppliers to coordinate, and also sit between many paths in the network, connecting parts production. This is reflected by the large range of products they produce, from military and defense products, to medical equipment, fuel cells, to elevators. This of course means a diverse portfolio of suppliers to manage for integrating multiple parts into various products. These two companies have tertiary dealings with the other sector producers although their aerospace divisions supply directly to Airbus, they may be affecting the network through other divisions. Eaton Corporation is the most operationally critical company, whose portfolio reflects the three main industrial clusters in the network: electronics, automotive and aerospace. Eaton is critical in distribution of goods in the network, and any disruptions to it would affect the entire network.

NHK Spring has the highest closeness centrality and produces automotive components. Although mainly a second tier Japanese supplier from the perspective of Airbus, it is close to rest of the network and has the ability to affect the whole network through the automotive sector and is therefore critical.

5 Discussion

The research has shown an emergent, complex network. Firms in the supply network have asymmetric information and access to resources, due the complexity of the network structure. Firms cannot see the whole picture of production manufacturing process, because of the restriction of technologies from competencies protection or government policy.

The structural analysis of Airbus supply network has shown that other OEMs such as Boeing and Lockheed Martin have indirectly connected to it. Moreover, it appears that, at least structurally, the influence of US companies is more crucial than the European firms. The position and the influence of three large Aerospace firms (Boeing, Airbus, Lockheed Martin) are quite similar in the network, as they are sharing the same aerospace resources in the world in terms of the metrics we analysed the network with, and its topology.

The supply network of Airbus appears to have tight connections with Boeing and Lockheed Martin these OEM firms, that indicates the suppliers in network is relied on by them due to their advanced and reliable technologies and components. For instance, both Boeing and Airbus require their suppliers get Nadcap Accreditation in specialized manufacturing field, such as Non Destructive Testing, Electronics and Non-metallic material test. Such restricted accreditation makes a quite high threshold for suppliers, in that case only few capable firms can join the group, and also that makes them powerful in Aerospace industry. The network thus shows low density, but high clustering between prominent firms.

Some of firms are involved in different industries concurrently; this is especially true for automotive and aerospace. From the network topology it is obvious that aerospace industry is densely connected to the automotive industry which itself is geography influenced (mostly concentrated in Japan and Europe). Hence automotive disruptions in special regions may cascade to aerospace as well.

Raw material suppliers, particularly in Rubber and Aluminium industry, are very few in the supply network. These resources are held by large multinational conglomerates. Airbus may be vulnerable when one of them fails to deliver. Although each failure strategy can damage the connectivity and topology of network to a certain extent, none of them make the properties of network dramatically fall at one go, hence Airbus supply network is robust, Failure happens when the network is attacked repeatedly, which might mean that in real life Airbus may have time to respond to maintain the order of production. Of course, this is a structural consideration only, and resilience will be determined by a combination of dynamic attributes such as inventory, capacity, cost of remodification, and the ability to overcome socio political and socio economic challenges.

It has been showed that the combination of empirical data and network analysis can bring new insights into supply chain analysis. On the other hand, the data is limited for there is no product information in the data flow.

Using revenue as the strength reflects the financial relationships among firms indeed; however it cannot represent the extent of dependency between two firms accurately; because the revenue depends on not only the capital of firms and the value of transaction between them, but also the products they are dealing. For example, a small firm can provide very limited resource but very crucial in the network, even the revenue is quite small, the influence in the network may be high. Therefore, for getting more practical results the database must be enhanced with product flow data.

6 Conclusions and Future Work

The research started by collecting empirical data to construct four tiers of a large scale aerospace supply network – that of Airbus, Airbus was chosen as an exemplary case study for the application of network science to extract structural features of complexity in supply networks, due to its scale, and reported complexity. After comparing with different databases, Bloomberg was chosen as the provider for collecting large-scale aerospace industry supply chain data. After cross checking with the annual reports, official publication and Internet resources, the data were validated (section 3). The structure of network was analyzed using hierarchy, degree distribution, robustness, geography and sector distribution, and connectivity analysis (Section 4). Key firms were identified in section 4.3.

Airbus supply network shows similar scale–free network behaviours just like other real complex social network. This point also is proved by the robustness properties under nodes failures. The network is robust to random failure but vulnerable to hub failures, meantime highlighted the key firms in the network combining the results of node-level parameter results. Community features is detected in the network, and the communities emerge to establish along with the same sector and same geography location. Hence the firms connecting different region or sectors play significant role to associate the different communities and maintain the integrity of the supply system. From weighted network perspective, the firms with high topological features can control and attract more market share and financial support, which improve the impact further in the aerospace industry. This study supports the result of OEMs becoming more dependent on a few suppliers in literature as well.

Given above structural features, we find that the Airbus supply network will be damaged quickly if key firms are disrupted. But due to the trend of stable decrease in disruptions, Airbus supply network would have time to recover the supply system before it crashes badly, if the network disruptions were visible. Moreover, adding more connections among these firms will improve the robustness of network. Applying risk-sharing and joint venture strategies could enhance the strength of ties between highly connected firms.

This is just a beginning the study of aerospace industry supply chain management using network analysis, there are still more further research to do, Creating an optimized database is critical, in which there should be not only listed firms but all the firms involved in the aerospace production process, including those that are not directly related to the aerospace manufacturing but serving the industry. It is important to increase visibility and understand what kinds of roles exist in the supply network.

The sector information does not contain actual products in the chain, which would be helpful to understand more detailed properties of aerospace industry if the transaction information is known.

Network analysis has many more methods to analyse features of supply networks, and only a small subset in this research has been used. Many other methods such as PageRank, Neighbourhood overlap and embeddedness could be helpful in providing new insights by identifying firms' network positioning and resulting span of control. Finally, it is important to study other types of complex supply network structures for comparison and generalisation. Whether network structures can be optimised in an emergent supply chain remains an open question.

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