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CLOUD-BASED DESIGN AND MANUFACTURING SYSTEMS: A SOCIAL NETWORK ANALYSIS

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ABSTRACT
A Cloud-Based Design and Manufacturing (CBDM) System refers to an information and communication technology (ICT) system that facilitates design and manufacturing knowledge sharing between actors (e.g., CBDM service providers and consumers) in the distributed and collaborative socio-technical network. The aim of this study is to address the challenge of information sharing and technical communication during the CBDM product development process. Specifically, we model a CBDM system as a socio-technical network. The research questions are: (1) What measures can be used to analyze the socio-technical network generated by CBDM? (2) How to detect communities/clusters and key actors in the socio-technical network? To answer these questions, a social network analysis (SNA) approach is formulated to analyze the socio-technical network generated by CBDM systems. The results indicate that SNA allows for visualizing collaborative relationship patterns of actors as well as detecting the community structure of CBDM systems.

Keywords: cloud-based design and manufacturing, socio-technical network, social network analysis, information sharing, communication

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1 INTRODUCTION

In academia and industry, the Pahl and Beitz's design method (Pahl and Beitz, 1988) and Suh's Axiomatic Design theory (Suh, 2001) are some of the most widely accepted design methodologies. Pahl and Beitz describe a product development process as a series of core transformations, from problem description to requirements list, to principal solutions and working structures, to preliminary design, to detailed layouts, and to final layout, form/dimensions, and manufacturing specifications. The design activities are classified into: product planning, conceptual design, embodiment design, and detail design. Suh's Axiomatic Design is based on matrix methods to analyze the transformation of customer needs into functional requirements, design parameters, and process variables. The major disadvantage of the traditional design processes is lack of interaction with stakeholders and crowds outside organizations (Howe, 2006).

Nowadays, companies have embraced social networks by using Facebook, LinkedIn, and Twitter as a media for interaction and communication with users and customers (Forbes, 2011). An IBM survey recently found that successful organizations are 57 percent more likely than other companies to provide their teams with social networking tools. McKinsey also found that well-networked organizations delivered higher market share and profits than less-networked companies (Bughin and Chui, 2010). Moreover, the biggest value that socio-technical networks offer goes beyond being marketing channels to push communication to prospects and customers (Franke et al., 2006). They also serve as new channels for collaboration and innovation. One good example is Yammer Inc. (2012), a so called "Facebook for the workplace", which is designed for team collaboration, file sharing, and knowledge exchange which enables seamless collaboration by bringing together people, content, and conversations across the entire product development process. The other example is Kenandy's "social manufacturing" platform (Kenandy, 2012), which has built the core manufacturing applications on a social platform which provide new tools of social media and collaboration for greater efficiencies in global supply chain networks (Kleinberg, 2008).

In line with the social network in working environment, cloud-based design and manufacturing (CBDM) has recently been proposed by Tao et al. (2011), Xu (2012), Wu et al. (2012), Wu et al. (2013), and Schaefer et al. (2012). According to Wu et al. (2012), CBDM refers to a product development model that enables collective open innovation through social media between service providers and consumers. From a social network perspective, in order to identify the information, knowledge and resources that are available in the socio-technical network of CBDM systems, it is essential to understand the collaboration structure and to detect communities in the socio-technical network of CBDM systems. In this paper, we want to address the following research questions:

1. *What measures can be used to analyze the socio-technical network generated by CBDM?*
2. *How to detect communities/clusters and key actors in the socio-technical network?*

In the next section, we present the related work on CBDM, SNA and community detection. Section 3 presents a holistic view of CBDM systems. Key measures in SNA that are used to investigate the socio-technical network generated by CBDM are introduced in Section 4. Section 5 presents the data collected from two engineering design examples. In Section 6, the SNA measures from Section 4 are applied to the data in Section 5. We conclude the paper in Section 7 with a further discussion about the results and the answers to the research questions.

2 RELATED WORK

2.1 Cloud-Based Design and Manufacturing

Wu et al. (2012) and Schaefer et al. (2012) introduce a comprehensive definition and concept of CBDM as well as a first step towards understanding the key characteristics and fundamentals of it. A brief survey of related research and associated technologies is presented with a focus on the potential CBDM application fields such as collaborative design, distributed manufacturing, and knowledge management systems. They also point out several future challenge and opportunity associated with CBDM. Xu (2012) discusses the architecture, core enabling technologies, typical characteristics for cloud manufacturing, and the relationships between cloud computing and cloud manufacturing. He also suggests the potential of cloud computing that can transform the traditional manufacturing business models by creating intelligent factory networks. Two types of cloud computing adoptions in the manufacturing sector have been suggested, direct adoption of cloud computing technology in the IT area and cloud manufacturing where distributed resources are encapsulated into cloud services and managed in a centralized manner. Tao et al. (2011) propose a four stage cloud manufacturing model where manufacturing resources are controlled through the internet through intelligent monitoring systems. These resources are then virtualized and encapsulated into manufacturing cloud services. The proposed architecture consists of manufacturing resources and abilities at the lowest level. These resources are then virtualized and managed in a cloud environment, and then made available to consumers through an application layer. The functional layers of the architecture are facilitated by the layers of knowledge, cloud security, and a network such as the internet.

2.2 Social Network Analysis

In 1930s, Moreno's work led to the formalization of SNA (Moreno and Jennings, 1938). Afterwards, in 1950s, John Barnes first coined the term "social network". Granovetter (1973) developed the theory of "the strength of weak ties" as a means of linking micro- and macro-level theories in sociology. Wellman and Berkowitz (1988) were among the earliest researchers who incorporate the social network approach with computers. Haythornthwaite (1996) introduces SNA as an approach and set of techniques for the study of information exchange. Jensen and Neville (2002) study SNA using machine learning and data mining techniques and have developed methods for constructing statistical models of network data. Kim and Srivastava (2007) present an overview of the impact of social influence in E-commerce and suggest that the key issues need to be focused on, including how to combine social influence data into user preferences, and how to exercise social influence on customers' purchase decision making. Borgatti and Li (2009) discuss the potential of SNA for supply chain management by applying network concepts to both hard (e.g., material and money flows) and soft (friendships and sharing-of-information) types of ties. Gloor et al. (2009) introduce a novel set of SNA based algorithms for mining the Web, blogs, and online forums to identify trends and find the people launching these new trends. Lin et al. (2008) develop a social networking application, SmallBlue, that unlocks the valuable business intelligence of "who knows what?", "who knows whom?", and "who knows what about whom?" within an organization. The goal is to locate knowledgeable colleagues, communities, and knowledge networks in companies. Hassan (2009) demonstrates how SNA theory supports the task of designing IT-enabled business processes by providing social network measures for evaluating alternative process designs. These measures offer better information for process designers who are faced with making IT investment tradeoffs, especially as the process design task is being undertaken. Braha and Bar-Yam (2004) analyzed the statistical properties of real-world networks of people involved in product development activities and showed that complex product development networks exhibit the 'small-world' property meaning that actors can be reached from every other by a small number of steps.

2.3 Community Detection

The aim of community detection is to (1) identify the modules and their hierarchical organization; (2) detect customers with similar interests; and (3) create data structures to handle queries or path searches (Agrawal and Jagadish, 1994). The modern science of graph theory has brought significant advances to our understanding of complex networking systems. One of the most relevant features of graph theory is community detection or clustering, i.e., the organization of vertices in clusters, with many edges joining vertices of the same cluster and with comparatively few edges joining vertices of different clusters (Lancichinetti et al., 2009). Girvan and Newman (2002) proposed an algorithm aiming at the identification of edges lying between communities and their successive removal, a procedure that after some iterations leads to the isolation of the communities. In this seminal work, the intercommunity edges are detected according to the values of a centrality measure, the edge betweenness that expresses the importance of the role of the edges are transmitted across the graph following paths of minimal length. Identifying clusters of customers with similar interests in the network of purchase relationships between customers and products of online retailers, like Amazon, enables to set up efficient recommendation systems (Krishna Reddy et al., 2002), that better guide customers through the list of items of the retailer and help companies to improve their sales and profitability. Tyler et al. (2005) develop a methodology for the automatic identification of communities of practice from email logs by using the betweenness centrality algorithm. This approach enables the identification of leadership roles within the communities. Clauset et al. (2004) develop an algorithm for inferring community structure from network topology, which is applied to analyze a large network of co-purchasing data from Amazon.com.

3 A HOLISTIC VIEW OF CBDM

According to the CBDM concept proposed by Wu et al. (2012), we present a holistic view of CBDM that connects four types of CBDM services and their corresponding activities as illustrated in Figure 1.

Hardware-as-a-service (HaaS) delivers hardware sharing services (e.g., milling, lathe machines, CNC machining centers, hard tooling, and manufacturing processes) to cloud consumers. HaaS allows cloud consumers to have access to these manufacturing resources without purchasing them. In order to schedule the manufacturing resources in the cloud, their statuses (e.g., if the machine is idle or not and if it is in maintenance or not), are monitored in real-time through various sensors including RFID wireless systems, process control sensors, and vision sensors. The heterogeneous data collected by these sensors are stored in servers and data centers in the cloud for further processing and analysis.

Software-as-a-service (SaaS) delivers software applications, e.g., CAD/CAM, FEA tools, and Enterprise Resource Planning (ERP) software to cloud consumers. Cloud consumers are able to install and run engineering and enterprise software through a thin client interface without purchasing full software licenses. The cloud service offered by Dassault Systems (2011) and Autodesk (2011) are by far the best known examples among engineering analysis applications, allowing remotely running 3D software and high performance discrete computing environments.

Infrastructure-as-a-service (IaaS) provides consumers and providers with computing resources, e.g., high performance servers and data centers. These services are offered on a pay-as-you-go basis, eliminating downtime for IT maintenance as well as reducing costs dramatically. The "Big Data" collected from hardware and software resides in these servers and data centers.

Platform-as-a-service (PaaS) offers a social networking media for cloud consumers and providers to communicate and collaborate, providing a new channel for mass collaboration and open innovation. Specifically, the social network platform enables to information sharing and knowledge exchange by bringing together customers, market analysts, designers across the entire design and supply chain networks. The information and knowledge stored in the data centers and servers in IaaS.

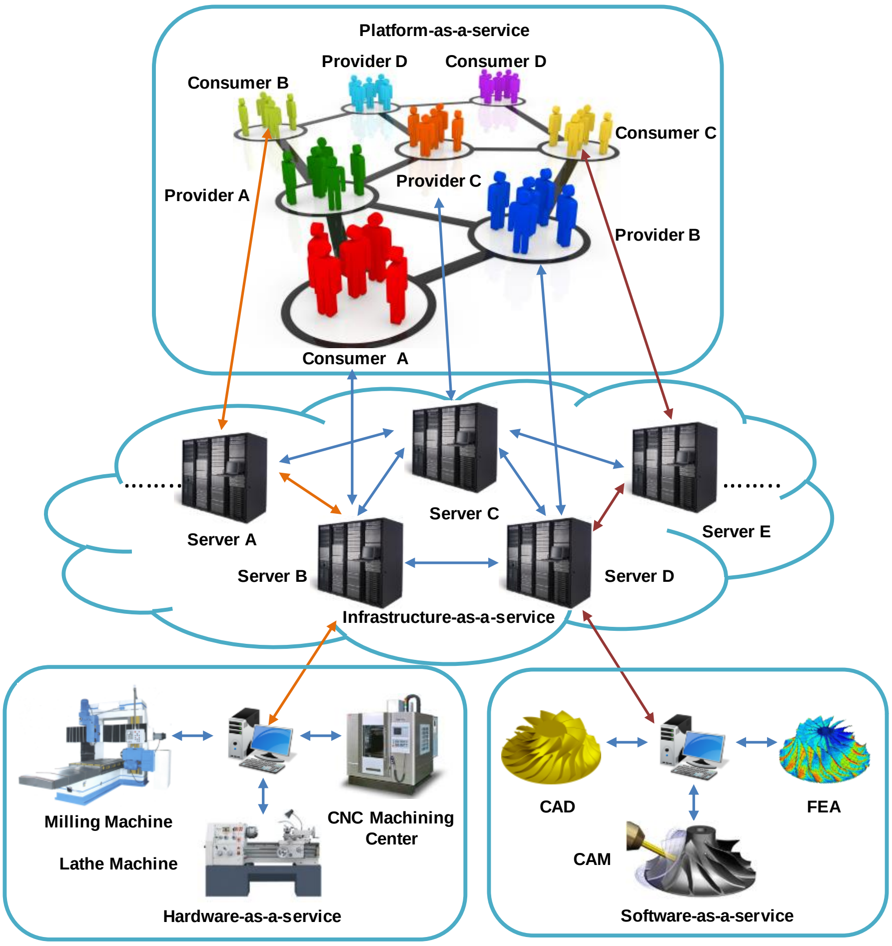


Figure 1. A holistic view of CBDM

4 MEASURES IN SOCIAL NETWORK ANALYSIS

The essential measures for SNA are centrality of the graph defined at the actor and group levels. They are designed to rank the actors according to their position in the network and interpreted as the prominence of actors embedded in a social network.

Degree: Degree of a vertex of a graph is the number of edges incident to the vertex.

Graph Density: Graph density is the average of the standardized actor degree indices as well as the fraction of possible ties present in the network for the relation under study. In other words, it measures how many edges in a graph compared to the maximum possible number of edges. Graph density takes on value between zero (0) (empty graph) and one (1) (complete graph).

Betweenness Centrality: Betweenness defines the extent to which an actor lies between other actors in the network. This measure takes into account the connectivity of the actor's neighbors, giving a higher value for actors which bridge clusters. The measure reflects the number of actors which the actor is connected indirectly through the direct links (Wasserman and Faust, 1994).

Actor betweenness centrality is defined as:

$$C'_B(n_i) = \frac{C_B(n_i)}{[(g-1)(g-2)/2]} \tag{1}$$

where $C'_B(n_i)$ is the standardized actor betweenness index for n_i. $C_B(n_i)$ is the actor betweenness index for n_i. g is the number of actors. The calculation of $C_B(n_i)$ is discussed in more detail in (Wasserman and Faust, 1994).
Group betweenness centrality is defined as:

$$C_B = \frac{2\sum_{i=1}^{g}[C_B(n^*) - C_B(n_i)]}{[(g-1)^2(g-2)]} \tag{2}$$

where C_B is the index of group betweeenness. $C_B(n^*)$ is the largest realized actor betweenness index for the set of actors.
Closeness Centrality: Closeness centrality defines the degree to which an actor is near all other actors in a network. It reflects the ability to access information through the grapevine of network members. Closeness centrality is the inverse of the sum of the shortest distance between each actor and every other actor in the network.
Actor closeness centrality is defined as:

$$C'_C(n_i) = \frac{g-1}{[\sum_{j=1}^{g} d(n_i, n_j)]} \tag{3}$$

where $C'_C(n_i)$ is the standardized index of actor closeness. $d(n_i, n_j)$ is the number of lines in the geodesic linking actors i and j. The details about how to calculate $d(n_i, n_j)$ can be found in (Wasserman and Faust, 1994).
Group closeness centrality is defined as:

$$C_C = \frac{\sum_{i=1}^{g}[C'_C(n^*) - C'_C(n_i)]}{[(g-2)(g-1)]/(2g-3)} \tag{4}$$

where C_C is the index of group closeness. $C'_C(n^*)$ is the largest standardized actor closeness in the set of actors.
Clustering Coefficient: Clustering coefficient of an actor is the ratio of number of connections in the neighborhood of an actor and the number of connections if the neighborhood was fully connected. Clustering coefficient identifies how well connected the neighborhood of an actor is. If the neighborhood is fully connected, the cluster coefficient is one. A value close to zero means that there are hardly any connections in the neighborhood of the actor. A higher clustering coefficient indicates a greater cliquishness (Wasserman and Faust, 1994). In other words, it is a measure of degree to which nodes in a graph tend to cluster together.

5 DATA

In this section, two engineering design examples are presented with a focus on data source and data collection. The data of both examples was collected from a graduate level course on engineering design, ME6102: Designing Open Engineering Systems, offered at the Georgia Institute of Technology. In addition, this is a 3 credit hours class which is equal to 3 hours per week. A minimum of 8 hours per week is required to be spent on a course project. Each semester is 15 weeks of class. Hence, we estimate that 120 hours were spent conducting the course project for each student.
The data was collected by interviewing individual students (actors), from both the on-campus and distance learning cohorts. One dataset was from the spring semester in 2011; the other was from the spring semester in 2012. The data were about who connects to whom during distributed and collaborative product development in the CBDM environment. The projects in these two examples were: Example 1 the design of wind-based electricity generation device; and Example 2 the design of hydroelectric footwear. The brief problem descriptions are the following:
Project brief for Example 1: "Many opponents to "Wind Farms" in open country base their objections on the disruption of windmills on the scenery, noise, and the possible environmental intrusion. Cities are, however, potentially just as windy as other locations. – Your task is to conceptualize, design, and prototype a device that generates electricity from wind for implementation on a building in a metropolitan environment. Use the principles of open engineering systems to create a flexible solution that can be adapted toward the creation of a product family. Identify varied customer requirements for this device and applicable markets (Atlanta initially followed by other U.S. cities). Determine the energy output of the device and perform a cost-benefit analysis and rapid prototype the final device design."
Project brief for Example 2: "A hydroelectric micro-generator powered footwear concept was developed and patented in 2001 which has the potential to change the way individuals power their personal electronics. The idea was to take small hydroelectric generators and utilize them in shoes to generate power. As the wearer of the shoes walks, the fluid contained within the internal passageways of the shoe will be forced to pass through a turbine and generate power. This power can potentially be used to charge or power personal devices such as

mobile phones, MP3 players, small computers, etc. The purpose of this project is to take the hydroelectric footwear concept from the idea stage to a breakthrough innovation."

These two examples were selected for two reasons. First, they were well-suited for demonstrating CBDM product development processes which involve a variety of information sharing tools for online community such as Google Groups, Google Docs, Skype, Dropbox, and Wiggio as shown in Table 1. The course was aimed at providing an opportunity for students to learn how to design a successful product by mass collaboration and collective decision making via online community and social media. Through such environment, the students were able to practice and experience real engineering design activities via a real industry project. Second, the projects conducted in the two examples were focused on engineering design problems; each entails the design and prototyping of a product.

Table 1. Communication tools and their uses

Communication Tools	**Uses**
Google Groups	Mailing list, group discussion
Google Docs	File sharing for simultaneous editing
Skype	Real time conversation
Dropbox	Cloud storage, file synchronization
Wiggio	Upload and manage big files, poll the group in real time, manage events and scheduling

We collected two types of data: actors and links, transformed them into a set of vertices and edges by identifying the number of actors and links where vertices represent actors and edges. In our two examples, the vertices represent students and the edges between two vertices reflect information and/or resource exchange relationships. For example, the edge between actors A and B is determined by the answer to true or false questions as follows:

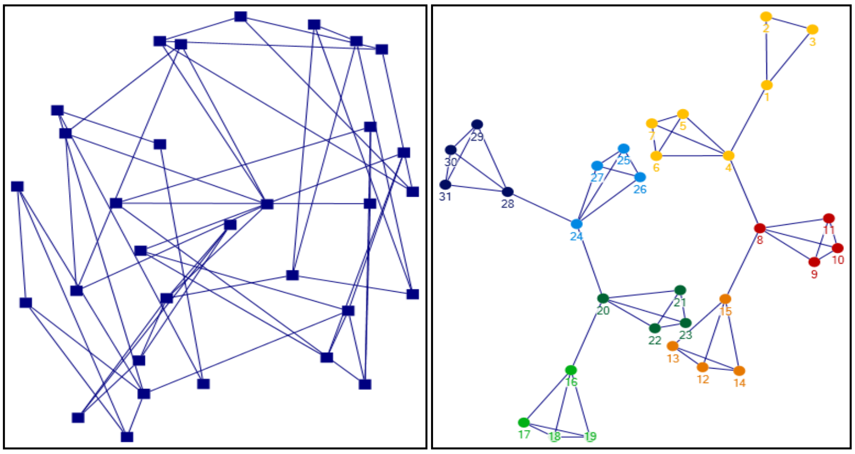
1. Is there any information received or sent by the actor A from or to the actor B?
2. Is there any materials received or sent by the actor A from or to the actor B?

Surveys and interviews allow us to capture the existence of the links between actors.

The data analysis was conducted using a SNA tool, NodeXL, developed by Smith's team at Microsoft Research (Smith et al., 2009). NodeXL is a free and open source network analysis add-in for Microsoft Excel that supports for exploring network graphs and information visualization.

6 RESULTS

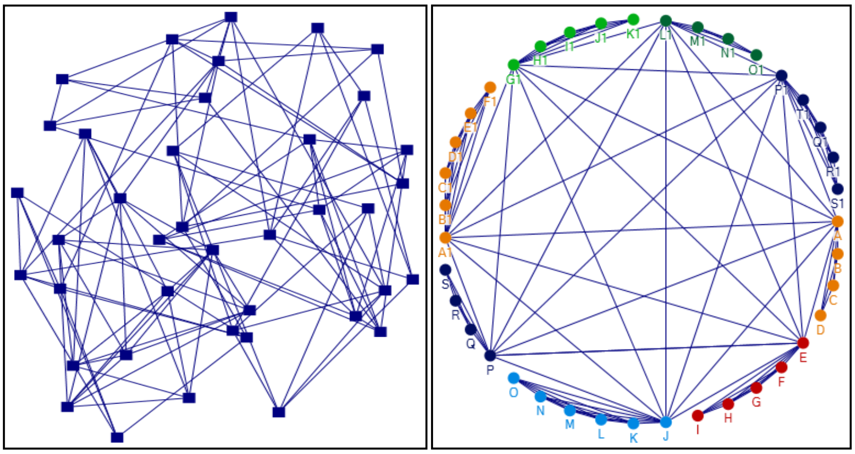
In this section, the SNA measures from Section 4 are applied to the data collected from Examples 1 & 2 in Section 5. Specifically, (1) the SNA measures were interpreted in the context of CBDM; (2) Groups and clusters were recognized from the interaction patterns in the data collected. Cluster leaders were identified using the SNA measures.



(a) Before community detection for Example 1 (b) After community detection for Example 1

<u>Example 1:</u>

As illustrated in Fig.2 (a) & (b), two separate groups with eight clusters of actors were successfully detected using SNA approach. Group 1 was composed of vertex 16 to vertex 31. Group 2 was composed of vertex 1 to vertex 15. The captured communication and interaction pattern followed that of the traditional product development process using Pahl & Beitz's method. Four clusters were detected for Group 1. The information flow started with the market analysis subgroup (vertices 28, 29, 30, and 31 in dark blue), to the engineering design subgroup (vertices 24, 25, 26, and 27 in light blue), manufacturing subgroup (vertices 20, 21, 22, and 23 in dark green), and to the production subgroup (vertices 16, 17, 18, and 19 in light green). Similarly, another four clusters were detected for Group 2. Since Group 1 and 2 were competitive groups, there was no communication between them. As a result, the two groups were not connected with each other. The general graph metrics and statistics for group centrality are listed in Tables 2 and 3. As shown in Table 4, for Example 1, 8 actors (vertices 1, 4, 8, 15, 16, 20, 24, and 28) are identified as the pivotal players in the information flow based on their relatively high betweenness scores in comparison with the average betweenness score: 12.355 as shown in Table 3.



(c) Before community detection for Example 2 (d) After community detection for Example 2

Figure 2. Community detection with Clauset-Newman-Moore algorithm (Clauset et al., 2004)

Table 2. General graph measures for Example 1 & 2 at the group level

Example 1		Example 2	
Graph Metrics	**Value**	**Graph Metrics**	**Value**
Vertices	31	Vertices	39
Unique Edges	51	Unique Edges	105
Total Edges	51	Total Edges	105
Maximum Vertices	16	Maximum Vertices	39
Maximum Edges	27	Maximum Edges	105
Graph Density	0.109	Graph Density	0.143

Example 2:

As shown in Fig.2 (c) & (d), the same four clusters of actors, i.e., (1) market analysts, (2) designers, (3) manufacturing engineers, and (4) production managers were successfully detected for two subgroups: A and B in one team, respectively. For subgroup A, the information flow started with marketing analysts (vertices A, B, C, and D in orange), to designers (vertices E, F, G, H and I in red), manufacturing engineers (vertices J, K, L, M, N, and O in light blue), and to production managers (vertices P, Q R, and S in dark blue). Similarly, another four clusters were detected for subgroup B. Subgroup A and B were connected with each other through subgroup leaders of the team (i.e., vertices A, E, J, P, A1, G1, L1, and P1) by utilizing some of the information sharing tools for online community described before. The general graph metrics and statistics for group centrality are listed in Tables 2 and 3. As shown in Table 4, for Example 2, 8 actors (vertices A, E, J, P, A1, G1, L1, and P1) are identified as the pivotal players in the information flow based on their relatively high betweenness scores in comparison with the average betweenness score: 27.000 as shown in Table 3.

7 DISCUSSION AND CONCLUDING REMARKS

In this section, we will answer the research questions raised in the introduction.

In terms of what metrics should be used to quantify the socio-technical network, we found that the general graph metrics in Table 2 and the statistics for group centrality in Table 3 at the group level provide insights for understanding the overall collaboration structure of the network. At the same time, some of the graph metrics at the actor (vertex) level are also very valuable to capture individual actor's role as shown in Table 4 including degree, betweenness centrality, and cluster coefficient. We found that the following metrics have been found to be important for understanding the overall collaboration structure:

- Vertices, Edges, Graph density;
- Betweenness centrality, closeness centrality, clustering coefficient at the group level;

Table 3. Statistics for group centrality for Example 1 & 2 at the group level

Example 1		**Example 2**	
Centrality	**Value**	**Centrality**	**Value**
Minimum Betweenness Centrality	0.000	Minimum Betweenness Centrality	0.000
Maximum Betweenness Centrality	68.000	Maximum Betweenness Centrality	165.000
Average Betweenness Centrality	12.355	Average Betweenness Centrality	27.000
Median Betweenness Centrality	0.000	Median Betweenness Centrality	0.000
Minimum Closeness Centrality	0.021	Minimum Closeness Centrality	0.010
Maximum Closeness Centrality	0.040	Maximum Closeness Centrality	0.016
Average Closeness Centrality	0.026	Average Closeness Centrality	0.011
Median Closeness Centrality	0.025	Median Closeness Centrality	0.010
Minimum Clustering Coefficient	0.300	Minimum Clustering Coefficient	0.470
Maximum Clustering Coefficient	1.000	Maximum Clustering Coefficient	1.000
Average Clustering Coefficient	0.840	Average Clustering Coefficient	0.898
Median Clustering Coefficient	1.000	Median Clustering Coefficient	1.000

Table 4. Graph measures for vertices for Example 1 & 2 at the vertex (actor) level

Example 1				**Example 2**			
Vertex	**Degree**	**Betweenness**	**Cluster Coefficient**	**Vertex**	**Degree**	**Betweenness**	**Cluster Coefficient**
1	3	24.000	0.333	A	10	105.000	0.533
4	5	57.000	0.300	E	11	136.000	0.491
8	5	61.000	0.300	J	12	165.000	0.470
15	4	33.000	0.500	P	10	105.000	0.533
16	4	36.000	0.500	A1	12	165.000	0.470
20	5	68.000	0.300	G1	11	136.000	0.491
24	5	68.000	0.300	L1	10	105.000	0.533
28	4	36.000	0.500	P1	11	136.000	0.491

In terms of how to detect communities and key actors in the socio-technical network, the results in Fig.2 suggest that the Clauset-Newman-Moore algorithm can detect the communities effectively. As illustrated in Fig.2 (a) and (b), the Clauset-Newman-Moore algorithm identified eight actors in Example 1 who have relative higher degree, betweenness centrality, and lower cluster coefficient at the actor level (as shown in Table 4) by comparing with the statistics for general metrics and centrality at the group level (as shown in Table 2 & 3). It turns out that the actors as shown in Table 4 (vertices 1, 4, 8, 15, 16, 20, 24, and 28) are subgroup leaders who communicate with other actors more often, and have access to more information and resources. The same conclusion holds in Example 2. As illustrated in Fig.2 (c) and (d), there are also eight subgroup leaders (vertices A, E, J, P, A1, G1, L1, P1) but with higher betweenness and closeness centrality than those of subgroup leaders in Example 1 due to the fact that more communications (e.g., data exchange, file sharing, online group discussion) between individual actors are enabled by the CBDM systems. We found that the following metrics have been found to be the most important for detecting communities and key actors:

- Degree;
- Betweenness centrality and clustering coefficient at the actor level;

Therefore, here are the answers to the research questions from Section 1:

1. *Vertices, Edges, Graph density, Betweenness centrality, closeness centrality, clustering coefficient at the group level can be used to analyze socio-technical networks generated by CBDM;*
2. *Degree, Betweenness centrality and clustering coefficient at the actor level can be used to detect communities/clusters and key actors in the socio-technical networks generated by CBDM.*

We have demonstrated how to apply SNA measures and community detection algorithms to visualize the collaboration structure, capture the key actors, and identify the collaboration community in the socio-technical network of CBDM systems. The research findings contributed to the body of knowledge in the sense that it interprets SNA metrics into the context of distributed and collaborative design and manufacturing networks. Specifically the findings of the study help us grasp fundamental insights into collaboration relationships in the socio-technical network formed in CBDM systems at macro and micro levels, involving detection of clusters of key service actors and measuring the power and importance of individual actor in terms of degree, betweenness centrality, and clustering coefficient. We acknowledged that our study has the following limitations: (1) the two case studies were small in scale; (2) we did not consider the weights that different edges may carry due to the type and importance of the information exchanged between two actors. Future research can be focused on addressing these two issues.

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