Application of Topological Network Measures in Manufacturing Systems

Till Becker

Abstract Manufacturing systems are complex networks of material flow. Complex network theory has been used as a descriptive and empirical research tool for various network types. However, due to the distinct origin of the various investigated networks (e.g., social networks, biological networks, the Internet), it is not clear if there is a meaningful application of network measures in manufacturing systems. This chapter investigates network modeling and network measures in manufacturing systems, and categorizes them according to their type of research.

Keywords Complex networks · Network modeling · Manufacturing systems

Introduction

Many real-life systems can be represented as networks or graphs, which consist in their basic form of nodes and links. Usually, nodes represent system entities, while links between them describe their interactions or dependencies. Network modeling has been applied to social, biological, geographical, traffic, and logistic systems, like, e.g., communication networks (Braha and Bar-Yam 2006), river networks (de Menezes and Barabási 2004), food chains in ecosystems (Williams et al. 2002), urban traffic (Lämmer et al. 2006), or supply chains (Meepetchdee and Shah 2007). This remarkably simple way of modeling allows for a quick and straightforward description of a complete system, even if it is highly complex. Analyzes and methods that have been developed for the application on networks can be used to gain a deeper understanding of the underlying system without additional modeling effort.

T. Becker (✉)
Global Production Logistics, School of Engineering and Science,
Jacobs University Bremen, Bremen, Germany
e-mail: t.becker@jacobs-university.de

H. Kotzab et al. (eds.), *Dynamics in Logistics*,
Lecture Notes in Logistics, DOI 10.1007/978-3-319-23512-7_4

The vast spread of the network modeling technique has not fully arrived in the discipline of manufacturing systems, although it has been applied in related disciplines like supply chain design (Meepetchdee and Shah 2007). Therefore, it is necessary to investigate, if network modeling and analysis is applicable in the research on manufacturing systems and which concrete network-related methods from other disciplines can be transferred to the engineering of manufacturing systems.

As the goal of research for industrial economic activity is to describe, analyze, and shape the processes in companies and their interactions with their environment, one can identify the three layers of research: descriptive, analytical, and pragmatic (Bea and Haas 2005). Figure 1 displays the application of complex network theory in manufacturing systems research and the connections to the research goals. The actual network modeling of a real manufacturing system (i.e. depicting a manufacturing system as a set of work station nodes connected by material flow links) is the *descriptive* part. The network model can be further used in the *analytical* part as the foundation for analyses based on network measures. The analyses lead to the development of optimization implications, which form, together with their implementation to the real manufacturing system, the *pragmatic* part of the research. The optimization solutions are either fed back to the Network Modeling stage for further analysis or to the real Manufacturing System stage for implementation. A peculiarity of the network approach in manufacturing systems is the existence of numerous previously developed tools in other science disciplines, which have been using network modeling for a long time. Consequently, research in manufacturing systems can make use of an existing "Network Analysis Toolbox."

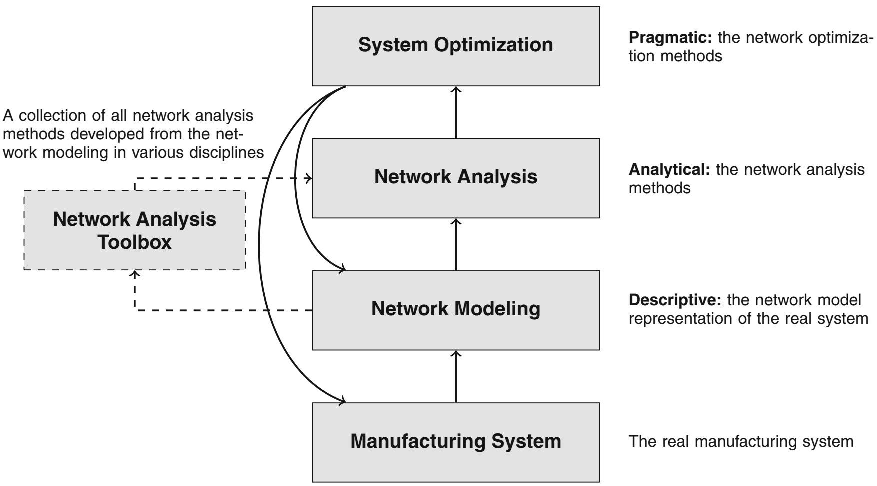

Fig. 1 The utilization of complex network modeling and analysis for manufacturing systems

The research questions addressed in this paper are:

- Can network measures be applied in descriptive, analytical, and pragmatic research on manufacturing systems?
- What are promising fields of further research in the area of network measures for manufacturing systems?

The remainder of this paper is structured as follows: the subsequent section introduces networks as a model for complex systems in general, presents a selection of basic network measures, and sketches the approach to model manufacturing systems as networks. The main part shows applications of centrality measures and subgraph analysis to real manufacturing system data, including a connection between network measures and system performance. The Conclusion Section interprets and summarizes the findings.

Complex Networks as a Modeling and Analysis Approach

Networks as a Representation of Complex Systems

Research on complex systems often uses approaches from graph theory or statistical mechanics (Albert and Barabási 2002), and can also be seen as an interdisciplinary field between those two research areas (Costa et al. 2007). Modeling systems as networks is part of graph theory, which originates from the work of Leonhard Euler in the eighteenth century. Contemporary network modeling and analyses focus mainly on the application of graph theory to highly complex systems. The development of information technology provides the possibility to collect, store, and process large amounts of data on the one hand, and offers enough computational power to perform statistical analyses, with this data, on the other hand (Albert and Barabási 2002). The combination of data availability, computational power, and methods from graph theory allow for the first time for a comprehensive analysis of topological (i.e. the network structure) and dynamical (i.e. the flow of elements through the network) features of complex systems from various sources. The comparison of evolved systems (e.g. biological or social systems) with anthropogenic, engineered systems is of particular interest, because the transfer of concepts like scalability, adaptability, self-organization, resilience, robustness, or reliability from evolved to engineered systems like manufacturing systems seems to offer promising optimization potential (Mina et al. 2006).

A network or graph consists of a set of nodes (or vertices) and a set of links (or edges) connecting pairs of nodes with each other, either unilateral (directed) or bilateral (undirected). If a complex system is modeled using the language of networks, it is necessary to define at least two things: (1) in which system elements are represented by nodes and (2) in which kind of interaction is depicted by links. Examples for complex systems modeled as networks are the World Wide Web (nodes: web pages, links: hyperlinks), the Internet (nodes: routers, links: connection between routers), telephone communication networks (nodes: persons, links: phone calls between persons), linguistic networks (nodes: words, links: adjacency relation of words in a text), and power networks (nodes: power plants and transformer stations, links: power lines) (Albert and Barabási 2002).

Topological Network Measures

If the descriptive part, the actual network modeling of a complex system, is concluded, an analytic assessment of the system is the next logical step. The network representation offers a variety of possibilities for analyzing the topological structure of the system. Common measures are centrality figures like degree or betweenness centrality, which quantifies how "central" a node is situated in the system, thus indicating its importance (Boccaletti et al. 2006). Each node in the network has a degree value, which indicates how many links are connected to this node. If a system is modeled as a directed network, the degree value can be split into the in-degree for the number of incoming links and the out-degree for the number of outgoing links. The degree distribution of the complete network reveals the relation between highly connected hub-nodes and rather isolated leaf nodes in the system.

Betweenness centrality (BC_v) of a node v indicates how many shortest paths traverse a node. The BC of a node is computed as the number of shortest paths σ between any pair of nodes i and j, that pass through the observed node, normalized by the total number of shortest paths between the two nodes (Freeman 1977).

$$BC_v = \sum_{ij} \frac{\sigma(i, v, j)}{\sigma(i, j)} \tag{1}$$

The advantage of BC over the degree is the consideration of paths, which also assign high BC values to nodes having less direct connection (thus a small degree), but, e.g., serve as a bridge between two network parts. Again, the distribution of BC values over the network can expose distinct structural characteristics of the entire system. BC can, e.g., be applied in manufacturing systems for anomaly detection (Vrabič et al. 2013).

A different way of assessing topological characteristics of a network is the determination of occurrence of network motifs. Motifs are 3-node subgraphs, and counting their occurrence in the network shows if there are prevalent local material flow patterns in a system, e.g., branches or confluences. An additional application scenario for motifs is categorization. Several studies have used network motifs to categorize complex systems by their motif pattern, especially in research on metabolic processes (see, e.g., Milo et al. 2004; Shen-Orr et al. 2002). In the field of logistics, Hammel et al. (2008) used the motif pattern of luggage handling systems for optimization purposes.

Manufacturing Systems as Networks

As mentioned earlier, there is a lot of scientific activity regarding network modeling and analysis in various disciplines, except for research on manufacturing systems, where network applications are sparse. There are more applications in the related field of supply chain due to the intrinsic network structure of supplier relationships in global manufacturing and trade (see, e.g., Xuan et al. 2011; Sun and Wu 2005; Meepetchdee and Shah 2007).

Existing network modeling approaches in manufacturing systems are the identification of autonomous clusters on a shop floor (Vrabič et al. 2012), anomaly detection in a shop floor (Vrabič et al. 2013), cross-disciplinary comparison of flow networks (Becker et al. 2011), and robustness evaluation of manufacturing systems (Becker et al. 2013).

The base frame for a manufacturing systems network model is the assignment of the manufacturing systems elements to the network elements. A manufacturing network (the network model representation of a manufacturing system) is a graph that consists of a set of nodes and a set of links. Each work station (i.e. machine, assembly station, quality gate, etc.) in the manufacturing systems is a single node, and each possible material flow between two work stations is a link, if at least one product or semi-finished product is routed directly between the two work stations. Depending on the desired granularity of the model, links can be either binary (i.e. present or not present) or assigned a link weight indicating the number of objects that are routed between the work stations. This basic network representation of a manufacturing system can usually be easily derived from scheduling data or production feedback data (see Becker 2012; Becker et al. 2013).

Network Measures in Manufacturing Systems

As pointed out in the previous section, network measures have been used in other disciplines to quickly assess and characterize complex systems according to certain topological features. Furthermore, it has been shown that manufacturing systems can be modeled as networks. The remainder of this section presents four analyses based on network measures involving manufacturing system network models derived from the feedback data of production control software. Table 1 summarizes the raw data collected from the six companies.

Table 1 Summary of the company datasets used in the network analyses

Company	Type	No. of operations	Company	Type	No. of operations
A	Job shop	77,119	D	Process	175,609
B	Job shop	28,294	E	Customizing	504,825
C	Job shop	60,081	F	Job shop	2329

Centralized or Decentralized Structures: Distribution of Node Degree

The individual degree of a node indicates how many connections to other elements exist in the system. In a manufacturing system setting, this means how many other work stations are predecessors or successors in material flow. The distribution of the degree values over the complete network reveals, if the material flow is rather equally distributed among the work stations or if there is a strong hub-and-spoke architecture in the system. The Lorenz curves displayed in Fig. 2 show that there are visible differences between the degree distributions of the manufacturing systems, some of them having a stronger separation between highly connected and less connected nodes and some not.

The random networks in Fig. 2 are networks generated using the Barabási-Albert preferential attachment model with the same amount of nodes and links as their corresponding company network (Barabási and Albert 1999). The conclusion from the comparison between the pairs of company networks and random networks is that manufacturing systems make up distinct networks with a stronger hub-and-spoke topology than one would expect from generic networks of the same size.

Identification of Central Nodes: Betweenness Centrality

Due to the consideration of paths in the network, in contrast to the determination of the degree based on neighboring nodes, the BC includes the complete network topology when measuring the importance of a node. Again, the inequality of the

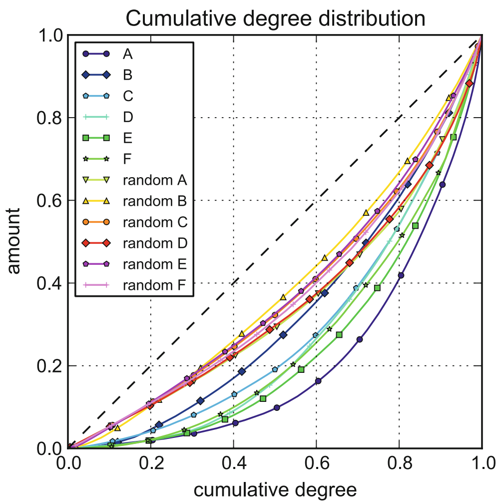

Fig. 2 Cumulative degree distribution of the manufacturing networks in comparison to randomized networks derived from the manufacturing networks (Figure adapted from Becker 2012)

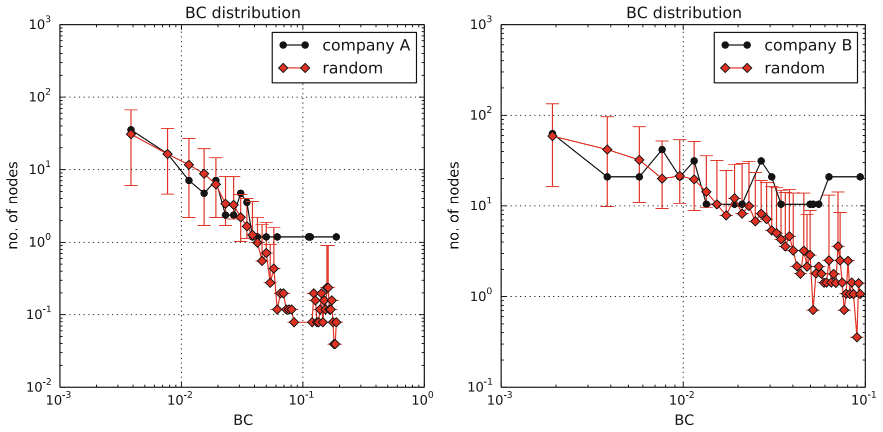

Fig. 3 BC distribution of company networks and respective random networks. For reasons of space, only companies A and B are shown (Figure from Becker 2012)

distribution of the centrality of nodes in the complete network becomes apparent in Fig. 3. A small number of highly central nodes face a high number of less connected nodes. This time, the random networks in the figures are derived from the original network by using a degree-preserving link switching algorithm: two pairs of connected nodes are selected randomly and their link targets are switched. This switching is repeatedly applied to the network. The result is a network, where every node still has the same degree, but the paths through the system have changed. It can be observed in Fig. 3 that the frequency of nodes with a low BC value does not deviate from the random, "natural" occurring scheme (the frequencies are inside the 0.2 and 0.8 quantiles of 30 randomly derived networks). However, nodes with a particular high BC are clearly overrepresented. This strengthens the previously gained insight from the degree distribution analysis that manufacturing system topology is nonrandom and favors the occurrence of a few highly connected work stations (Becker 2012).

Patterns of Material Flow: Network Motifs

Network motifs are 3-node subgraphs, in which frequency of appearance in a network indicates how material flow is organized on a local scale between small groups of network elements. All possible 13 variants of directed links between three nodes are depicted below the *x*-axis in Fig. 4a. The major purpose is to use the motif count for classification of networks. The *z*-score (Milo et al. 2004) indicates how much the motif is over- or underrepresented.

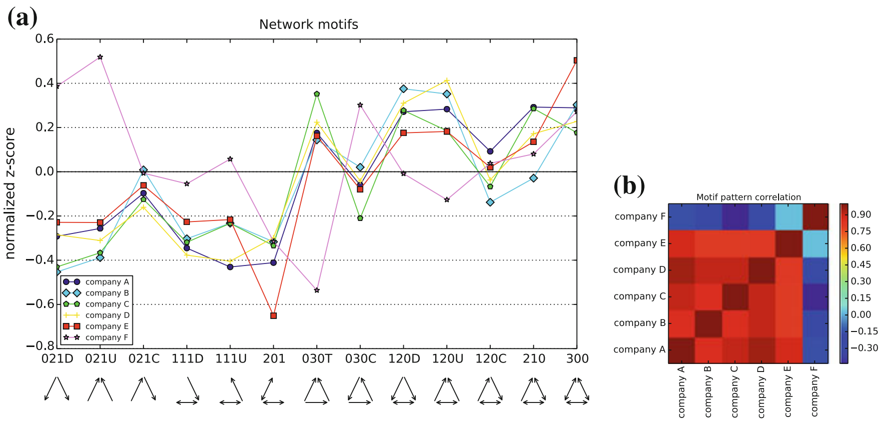

Fig. 4 Network motifs in manufacturing systems (Figure adapted from Becker 2012)

Figure 4a shows the motif z-scores for the company networks, and Fig. 4b shows the correlation among each pair of the 13-variate vectors. The high correlation among five of the six companies suggests that there is a distinct microscale material flow pattern in manufacturing systems, because other network types show different motif patterns (Milo et al. 2004; Becker 2012). Only company F deviates from this pattern, which is assumed to be caused by a high amount of unique products and individual repair orders.

Linking Network Measures and Performance: The Optimal Network Connectivity

A simulation study presented by Becker et al. (2012) using the six company networks as material flow networks investigated the relation between network topology and system performance in manufacturing systems. The study suggested that even for differing workload scenarios there is an optimal average network degree in the simulated manufacturing systems (see Fig. 5a).

The results of the simulation study could be reproduced when plotting the average work in process (WIP) against the average network degree in the real company datasets (see Fig. 5b).

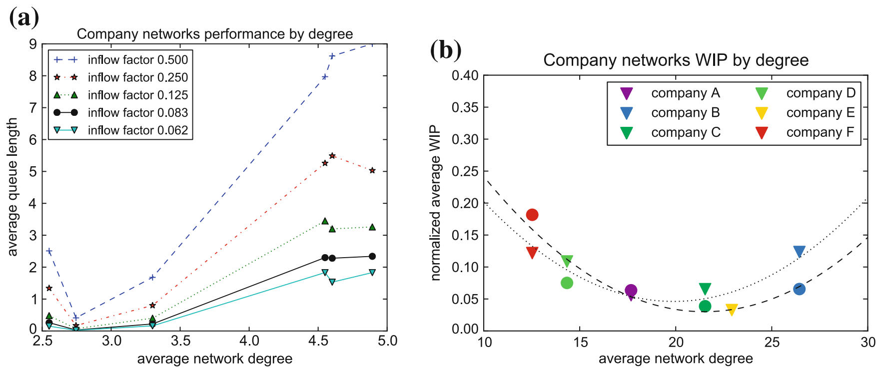

Fig. 5 **a** The material flow simulations based on the companies' manufacturing networks show that a network with an average degree between 2.5 and 3.5 has the lowest work in process (WIP) levels (indicated by the queue length at the work stations). **b** The same phenomenon is observed in the real company data, both using the number of orders as WIP (triangles) and the actual work content (*circles*). The *dotted* and the *dashed line* are the respective second degree least squares approximations (Figures adapted from Becker et al. 2012)

Conclusion

Network modeling and network analysis are widely used techniques in many disciplines for the research on complex systems. The first research question addressed the applicability of network modeling on descriptive, analytical, and pragmatic research in manufacturing. The answer is threefold: First, 11 application examples in this work use this way of modeling based on real company data. Therefore, one can state that network modeling is applicable for *descriptive* purposes in manufacturing systems. Second, the analyses of the distribution of the node degree and betweenness centrality, as well as the assessment of the motif count, show how network modeling satisfies the requirements for *analytical* research. Finally, making the link between manufacturing system performance and the topological structure of a manufacturing network represents a step toward the *pragmatic* research approach. However, additional work on descriptive and analytical research needs to be done in order to come up with mature pragmatic implications for manufacturing systems design and performance.

The network approach also has its limitations. As in every modeling attempt, the network model is a simplified representation of reality. The strength of network modeling, its minimalistic nature, is at the same time its weakness, because many features of the system are omitted. On the other hand, network modeling is flexible and extendable. Nodes and links can be perceived as objects that can carry additional information, e.g., capacities or priority rules, so that network modeling is not necessarily restricted to its simple form.

Further research is required to assign appropriate modeling techniques and analytical approaches to the network modeling framework presented in Fig. 1. The availability of network-related approaches from other scientific disciplines and the availability of large-scale manufacturing system data offer numerous possibilities to transfer these approaches to the realm of manufacturing systems.

References

Albert R, Barabási A-L (2002) Statistical mechanics of complex networks. Rev Mod Phys 74:47–97

Barabási A-L, Albert R (1999) Emergence of Scaling in random networks. Science 286:509–512

Bea FX, Haas J (2005) Strategisches management. UTB, Stuttgart

Becker T (2012) Parallels between manufacturing systems in industrial production and metabolic systems in biological cells: a network based unifying model from a production logistics perspective. Jacobs University Bremen, Bremen

Becker T, Beber ME, Windt K, Hütt M-T, Helbing D (2011) Flow control by periodic devices: a unifying language for the description of traffic, production, and metabolic systems. J Stat Mech Theor Exp 2011:P05004

Becker T, Beber ME, Windt K, Hütt M-T (2012) The impact of network connectivity on performance in production logistic networks. CIRP J Manufact Sci Technol 5:309–318

Becker T, Meyer M, Windt K (2013) A network theory approach for robustness measurement in dynamic manufacturing systems. The annual cambridge international manufacturing symposium, 19–20 Sept 2013

Boccaletti S, Latora V, Moreno Y, Chavez M, Hwang D-U (2006) Complex networks: structure and dynamics. Phys Rep 424:175–308

Braha D, Bar-Yam Y (2006) From centrality to temporary fame: dynamic centrality in complex networks. Complexity 12:59–63

Costa L, Rodrigues F, Travieso G, Boas P (2007) Characterization of complex networks: a survey of measurements. Adv Phys 56:167–242

De Menezes MA, Barabási A-L (2004) Fluctuations in network dynamics. Phys Rev Lett 92:028701

Freeman LC (1977) A set of measures of centrality based upon betweenness. Socicometry 40:35–41

Hammel C, Flemming A, Schulze F, Peters K (2008) Anwendung von Methoden aus der Theorie Komplexer Netzwerke für die Optimierung der Layouts von MFS. In: Subbert S (2008) 4. Fachkolloquium der WGTL an der Universität Chemnitz, WGTL, pp 81–91

Lämmer S, Gehlsen B, Helbing D (2006) Scaling laws in the spatial structure of urban road networks. Phys A: Stat Mech Appl 363:89–95

Meepetchdee Y, Shah N (2007) Logistical network design with robustness and complexity considerations. Int J Phys Distrib Logist Manag 37:201–222

Milo R, Itzkovitz S, Kashtan N, Levitt R, Shen-Orr S, Ayzenshtat I, Sheffer M, Alon U (2004) Superfamilies of evolved and designed networks. Science 303:1538–1542

Mina A, Braha D, Bar-Yam Y (2006) Complex engineered systems: a new paradigm. In: Braha D, Mina A, Bar-Yam Y (2006) Complex engineered systems, Springer, Berlin

Shen-Orr S, Milo R, Mangan S, Alon U (2002) Network motifs in the transcriptional regulation network of *Escherichia coli*. Nat Genet 31:64–68

Sun H, Wu J (2005) Scale-free characteristics of supply chain distribution networks. Mod Phys Lett B 19:841–848

Vrabič R, Husejnagić D, Butala P (2012) Discovering autonomous structures within complex networks of work systems. CIRP Ann-Manuf Technol 61:423–426

Vrabič R, Škulj G, Butala P (2013) Anomaly detection in shop floor material flow: a network theory approach. CIRP Ann-Manuf Technol 62:487–490
Williams RJ, Berlow EL, Dunne JA, Barabási A-L, Martinez ND (2002) Two degrees of separation in complex food webs. Proc Natl Acad Sci 99:12913–12916
Xuan Q, Du F, Li Y, Wu T-J (2011) A framework to model the topological structure of supply networks. IEEE Trans Autom Sci Eng 8:442–446