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A network theory approach for robustness measurement in dynamic manufacturing systems

Till Becker, Mirja Meyer, Katja Windt
Jacobs University Bremen, Global Production Logistics Workgroup
Campus Ring 1, 28759 Bremen, Germany
Fax: +49 421 200 3078, E-Mail corresponding author: mi.meyer@jacobs-university.de

Abstract
Robustness is a key characteristic of manufacturing systems that are embedded in highly fluctuating environments. These fluctuations are caused by short-term demand changes, changing customer requirements, or disruptions in the supply chain, such as delivery delays or material shortages. In order for a company to stay competitive and profitable, the performance of a manufacturing system should not significantly deviate in the face of such fluctuations, i.e. the manufacturing system should display a robust performance. Therefore, different approaches to measure and implement robustness in manufacturing systems have been proposed (Telmoudi et al. 2008; Feng 2009). In this paper we present a new approach on how to assess manufacturing system robustness using graph-theoretical network measures. We further analyze the quality of a specific robustness network measure under dynamic conditions (i.e. changing customer demand).

Keywords: **robustness, network measures, manufacturing, job-shop**

1. Introduction

As complexity in manufacturing systems rises (increasing variety of machines, higher amount of process steps due to more sophisticated products), failures such as machine errors or material shortages are more likely to propagate through the network of machines or work stations in a manufacturing system. This can lead to under-utilization, due date delays or quality defects, i.e. a decrease in overall performance. Robustness, which in general can be described as a system characteristic which “enables the system to maintain its functionalities against external and internal perturbations” (Kitano 2004), thus seems a desirable system characteristic for a manufacturing system on the system level. Various approaches exist to incorporate robustness in different aspects of manufacturing, e.g., robust production control, robust production planning & scheduling or robust capacity design (Tolio et al. 2011; Goren & Sabuncuoglu 2009; Toonen et al. 2012).

In complex network science, graph-theoretical network measures have proven to be a suitable tool to analyze the characteristics of different types of natural or man-made networks (Albert & Barabási 2002; Boccaletti et al. 2006). One of the many network characteristics that researchers in this field have focused on in the past is network robustness (Barabási 1999; Callaway et al. 2000; Jeong et al. 2000). It has recently been suggested to apply such network measures to classical manufacturing problems, such as machine grouping (Vrabič et al. 2012), since the network of machines in a manufacturing system can be depicted from a graph-theoretic point of view (machines=nodes, material flow=links).

However, measuring robustness as a static constant over time seems inappropriate for manufacturing systems. As it was found for other real-world systems (Braha & Bar-Yam 2006), the investigated nodes of the network (in our case a node represents a work station in the manufacturing system) seem to change their roles over time. We therefore investigate the appropriateness of a proposed network measure for robustness in manufacturing systems under dynamic conditions.

2. Robustness in Manufacturing Systems

Robust production control methods are control methods to organize release and routing of production orders in a way that fluctuations and disturbances do not negatively influence the performance of the manufacturing system. In (Telmoudi et al. 2008), a framework for robust control laws in manufacturing is suggested and manufacturing system robustness is defined as "its aptitude to preserve its specified properties against foreseen or unforeseen disturbances". Tolio et al. present a framework for robust production control in which they suggest to consider uncertainties when scheduling local resources (Tolio et al. 2011). Other approaches suggest methods for robust planning and scheduling of production orders. Such methods provide production schedules that anticipate potential fluctuations and disturbances and thus result in a better performance under uncertainty. In (Kouvelis et al. 2000), the authors define the task of robust scheduling as "determining a schedule whose performance (compared to the associated optimal schedule) is relatively insensitive to the potential realizations of job processing times" and they develop an optimization approach to hedge against uncertainty of processing times. Goren and Sabuncuoglu (2008) define "a schedule whose performance does not significantly degrade in the face of disruption" as being robust, propose performance measures for the robustness of schedules and further analyze the quality of the proposed measures using a tabu search-based scheduling algorithm. Another approach suggests determining robust production plans by integrating constraints in the stochastic capacitated lot-sizing problem, to ensure that a specific target customer service level is met with high probability (Nourelfath 2011).

Determining the long-term adequate amount of resources in a manufacturing system in a way that the system is rendered robust against certain influencing factors can be described as robust dimensioning or robust capacity allocation. Scholz-Reiter et al. (2011) use a queuing network which they approximate by a fluid model to measure robustness of capacity allocations using the stability radius (a measure commonly used in fluid networks). The stability radius describes the smallest change of parameter that destabilizes a system. In a more holistic approach, we previously suggested to consider robustness in manufacturing systems as an overall system characteristic rather than in terms of schedule performance, and thus to measure it in terms of logistics performance values of the entire system, such as due date reliability, throughput-times or utilization (Meyer et al. 2013).

3. Assessing System Robustness using Network Measures

A network and its elements can be easily represented as a mathematical graph, i.e. as vertices (nodes) and edges (links). Therefore using graph theoretical or statistical mechanics measures to investigate networks has become increasingly popular in the last decade. Research in this field has identified different network models, such as small-world (Watts & Strogatz 1998) or scale-free networks (Barabási 1999). It has been also been revealed that these network models can describe a number of different real-life systems, such as the World Wide Web or social networks (Barabási 1999). Thus researchers in the past increasingly used complex network measures to extensively investigate the characteristics of different natural and man-made networks. One of the many characteristics of interest in this context is network robustness. It has been shown that e.g. scale-free networks display an unexpectedly high degree of robustness against errors (Albert et al. 2000; Callaway et al. 2000; Bollobás & Riordan 2004). In this context, robustness is measured as the change in network diameter (defined as the average minimal path length between any two nodes) when a small fraction of the networks nodes is removed (Albert et al. 2000). This approach has been taken up by several scientists in different fields, e.g. Jeong et al. (2000) observe in metabolic networks that they display insensitivity to the removal of random links, using also the network diameter as a robustness indicator.

But also the robustness of more economically oriented networks, such as worldwide supply chains, has been analyzed using complex network measures. Meepetchdee and Shah (2007) measure supply chain robustness as the extent to which the supply chain is still able to fulfill demand despite damage (removal of nodes) done to the logistical network. They find that in supply chains, a trade-off between robustness and both complexity and efficiency exists. A further suggested robustness measure for supply chains is the behavior of the average node degree of the network under node deletion (Xuan et al. 2011).

It has been argued in various approaches that the network of work stations in a manufacturing system can also be considered as a graph (with nodes representing work stations and links representing material flow) (Becker et al. 2013, to appear; Vrabič et al. 2012; Vrabič et al. 2013). In Liu et al. (2011), the authors suggest to measure the robustness of a manufacturing system by using the clustering coefficient and the average shortest distance. They implement these measures as objectives into a nonlinear optimization approach to find an optimal resource allocation with high robustness and low costs.

However, most of the presented approaches measure robustness as a static characteristic, i.e. they measure average network values (e.g., number of nodes) over a longer period of time. Yet is has been shown that in certain networks (e.g., social communication networks), the roles of the different nodes in the network change over time (Braha & Bar-Yam 2006). In manufacturing networks, the links between the nodes (machines) represent material flow, which can vary drastically depending on the order spectrum in the analyzed time-span. Thus the significance of certain nodes for the robustness of the whole manufacturing network might also change dynamically. The aim of this paper therefore is to analyze what influence the dynamic behavior of the manufacturing system has on the quality of a suggested network measure for robustness in manufacturing systems.

4. The Manufacturing Systems Network Model

When we refer to manufacturing systems, we consider a set of work systems, which are interlinked by material flow among them. The work systems form a logical and organizational entity for the manufacturing of products and are usually also located close to each other, e.g. on a shop floor or on a production site. A work system can be any kind of physical or organizational treatment of material of products, e.g. a drilling machine, an assembly station, quality inspection, or a buffer.

The network representation of a manufacturing system is a directed graph $G = (V, E)$ that consists of a set of nodes (vertices) $V = \{v_1, \dots, v_{|V|}\}$ with the length of $|V|$ and a set of links (edges) $E = \{(v_i, v_j), \dots, (v_y, v_z)\}$ between a selection of node pairs with a length of $|E|$. Each work station in the manufacturing systems is a single node, whereas a material flow between two work stations is represented by a directed link (i.e. $\exists(v_a, v_b)$ if there is at least one product which is routed directly from v_a to v_b). This results in a binary representation of the material flow, regardless of its intensity. To add more information about the material flow, a link $(v_i, v_j) \in E$ can be assigned a link weight, which indicates how many products have been routed directly between the two work stations. The binary representation of links is sufficient to describe the topology of a manufacturing system network, so that analyses regarding connectivity, shortest paths, source-sink-relations, etc. can be conducted. If links are attributed a volume, the network model has a stronger emphasis on the operational processes in the system by quantifying the activity at each link.

The network modeling of a manufacturing system allows for the application of standard graph theoretic measures to describe the topology of a manufacturing system. As we focus on the robustness of manufacturing system, we restrict our description of possible key figures to those who are relevant for the robustness considerations we will suggest in the following.

The in-degree $deg^{-}(v)$ of a node v is the number of incoming links at a node and indicates to how many upstream resources a work station is directly connected. Similarly, the out-degree $deg^{+}(v)$ denotes the number of outgoing links and refers to the number of downstream resources that are linked directly to the observed work station. Consequently, the degree $deg(v)$ is the sum of incoming and outgoing links.

5. Manufacturing Systems as Dynamic Networks

The work systems of a manufacturing system and the material flow make up a directed network, because every material flow defines a mutual interaction between two entities of the system, for which a strict timely order exists. If we consider all material flows that have occurred in an observed time span, or if we consider all hypothetical material flows derived from the route sheets of the company's product portfolio, we get a static representation of the interactions within the manufacturing system. This network representation of the manufacturing system has a distinct topology, which can be the basis for further analysis. However, there is no dynamical component in this particular view on manufacturing systems. This is a major drawback of the static network approach, because manufacturing systems consist on the one hand of relatively persistent elements, the work systems, but on the other hand also of substantially temporal elements, namely the individual processes and operations on the network.

An extension of the previously presented network model is the consideration of the dynamic development of a manufacturing system over time. If we have an observation period from $1 \dots T$ with a time unit length of u, we are able to slice the observation period into T equally sized time bins. Now we can define a graph G_t for each $t = 1 \dots T$ with $G_t = (V, E_t)$. The set of links E_t now contains only links (v_a, v_b) if the material flow occurred in period t. The set of nodes remains unchanged, because the work systems are still part of the manufacturing system, even if there has been no in- or outbound material flow in the selected period.

6. Case Study

In our case study, we are going to address three main questions regarding robustness in dynamic manufacturing networks:

1. What is the appropriate time scale for the analysis of robustness in dynamic manufacturing networks?
2. How different are manufacturing networks in their time-dependent behavior?
3. How does the robustness of parts of the network develop dynamically over time?

Feedback data from the scheduling and control software of six different manufacturing companies serves as input data for our case. The six companies operate in tool manufacturing with a job-shop type manufacturing environment, in process industry, or in customization of cars. The observed time period is one year (company E: 3 months). Table CS1 shows a summary of the data sets.

Table CS1: Characteristics of the analyzed data sets. The number of work stations is indicated by the number of nodes in the network. The number of links depicts the number of material flow connections in the static network of the complete observation time.

company	**type**	**nodes**	**links**	**no. of operations**
A	job-shop	220	1944	77,119
B	job-shop	50	661	28,294
C	job-shop	102	1098	60,081
D	Process	197	1412	175,609
E	job-shop	102	364	2,329
F	customizing	87	999	504,825

Each data set consists of a list of all operations throughout the observed time period. Weekends have been removed from the data, except for company D, which operates 7 days per week. Each operation-record contains the ID of the operation's manufacturing order, the name of the work station the operation was performed on, and the time the operation was executed. We generate the network representation G of the manufacturing system by extracting all work systems and assigning them to the set V. The set E is filled with all material flows by extracting all pairs of worksystems from two consecutive operations of the same manufacturing order. Figure 1 depicts a graphical representation of the manufacturing network of company B over the entire observation period. Time-dependent network representations G_t are composed analogously, but by considering only the operations within period t when creating E_t.

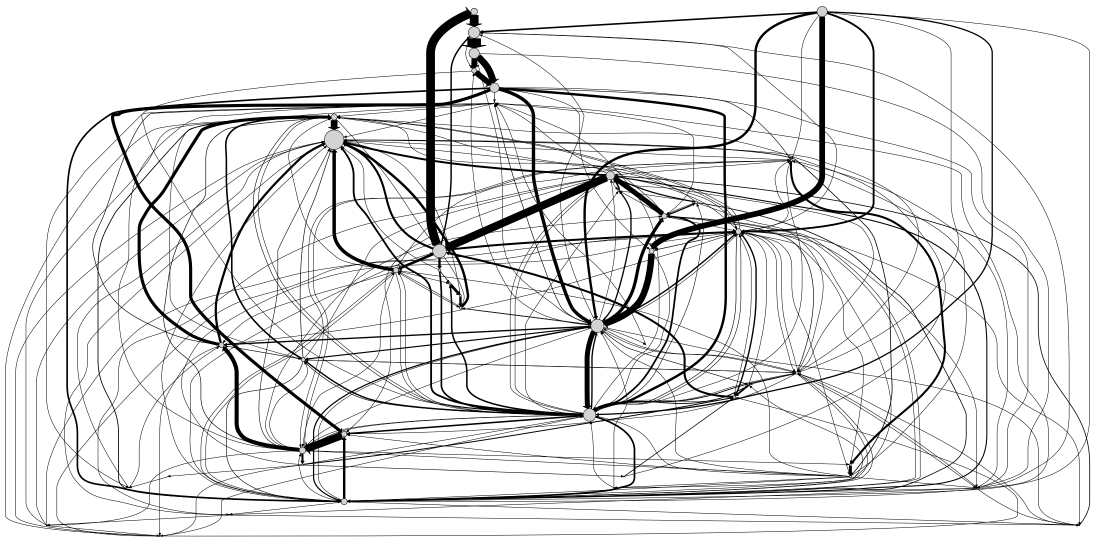

Figure 1 The network representation of company B's manufacturing operations. The line thickness indicates the edge weight, i.e. the number of material flows.

Our first question addresses the identification of an appropriate time scale for the analysis of manufacturing network dynamics. We selected the edge correlation as an indicator for network dynamics, as proposed by (Braha & Bar-Yam 2006) for the analysis of communication in a large social network. We compute the edge correlation by collecting the edge weights of all possible pairs of nodes for the selected time

periods in a vector and determining the correlation between all vectors. If there is no material flow between two nodes in a period, the edge weight is 0. Otherwise, the edge weight is the number of material flows in that period.
We select values of 1, 7, 14, 21, and 30 days for u and calculate the average for all correlations between each pair of vector elements to get the average edge correlation of a network for a certain time scale u. Figure 2 shows the results of our analysis. The first observation is that the dynamic networks statistics only differ significantly for small values of u, i.e. for $u = 1$. This means that if we slice the manufacturing operations into weekly, biweekly, or monthly periods, the material flows are highly similar. As opposed to this, a period of one day makes the networks distinguishable over time. Additionally, the average correlation at $u = 1$ strongly differs among the observed networks. The network pattern of companies A and B vary over time, while companies D and E show a relatively stable network pattern. Referring to our initial question, we conclude that only a small time scale, preferably of one day, is suitable for the analysis of dynamics in manufacturing systems.

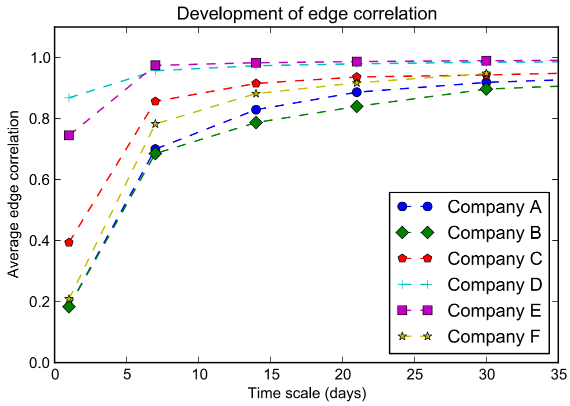

Figure 2: The network similarity, quantified by the average edge correlation, shows that a larger time scale impedes the identification of differences between different time periods of the same network. Only a time scale of 1 day reveals the dynamic development.

The second question focuses on the evaluation of the difference of manufacturing networks over time. The previous analysis has already partially answered this question by indicating that each manufacturing network can have a distinct, quantifiable level of similarity over time. To get a better impression of this phenomenon, we exemplarily visualize the edge correlation of company A and company D as correlation matrices in Figure 3.

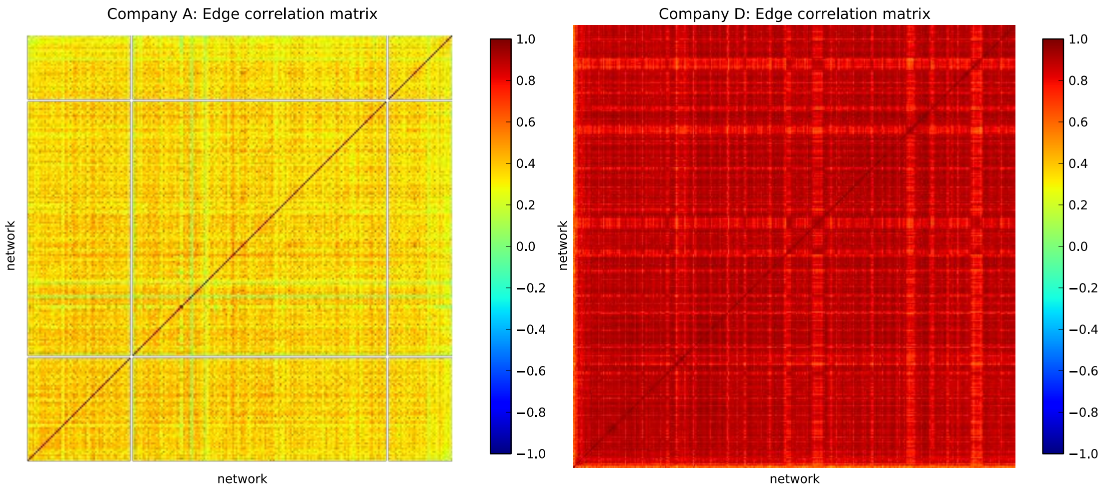

Figure 3: Edge correlation matrices for companies A and D for u=1.

The Figures 3a and 3b visualize the edge correlation for each possible combination of networks G_t. Both axes represent the range of time periods, in this case $t = 260$ for company A and $t = 365$ for company D. By definition, the correlation matrices are symmetric and have a value of 1 for all entries on the diagonal.

As expected from the data in Figure 2, company D exhibits a strong edge correlation of approximately 0.8 throughout the year, while the correlation values of company A are about 0.2 with occasional peaks towards 0.8. Regarding question 2, we state that edge correlation can be used to quantify the self-similarity of a manufacturing network over time. Moreover, the two plots underline the fact that manufacturing networks have a distinct similarity pattern with respect to their dynamic development over time. This implies that the impact of individual nodes on the network's robustness cannot simply be judged by an aggregated, static view of the manufacturing network, but requires an individual consideration depending on the diversity of the network over time.

Our final question aims at evaluating robustness in manufacturing networks over time. We introduce the ratio of remaining operations and overall operations after a node deletion as a robustness measure for the robustness of a network in terms of the deletion of a specific node. This key figure indicates how much a temporary breakdown of a single resource influences the productivity of the manufacturing network. Let o_t be the number of operations of a manufacturing network during period t and $o_{t,w}$ be the number of operations on work station w during period t. Then the robustness indicator $R_{t,w} \in [0,1]$ of the network in period t against the deletion of node w is:

$$R_{t,w} = \frac{o_t - o_{t,w}}{o_t} \tag{1}$$

Thus, a robustness value of 1 is perfect robustness, because the deletion of the selected node does not affect the operations during the observed period. The lower the robustness indicator, the more the complete network is affected by the deletion of node w.

First, we have determined the robustness value for the complete, static network (i.e. with a single period t covering the complete observation period) for each node. The frequency of robustness values for company B is plotted in Figure 4a. The figure illustrates that the individual deletion of a high number of nodes does not significantly affect the manufacturing network's robustness. Only the deletion of few nodes causes more severe disruptions of up to almost 10% of the operations. As a comparison, we plot the frequency of mean robustness after we perform the node deletion on each of the daily dynamic networks and average the robustness value over time. Up to this point, there is no visible difference between applying the measure to the static network or to average values of the dynamic networks. The other companies exhibit similar results.

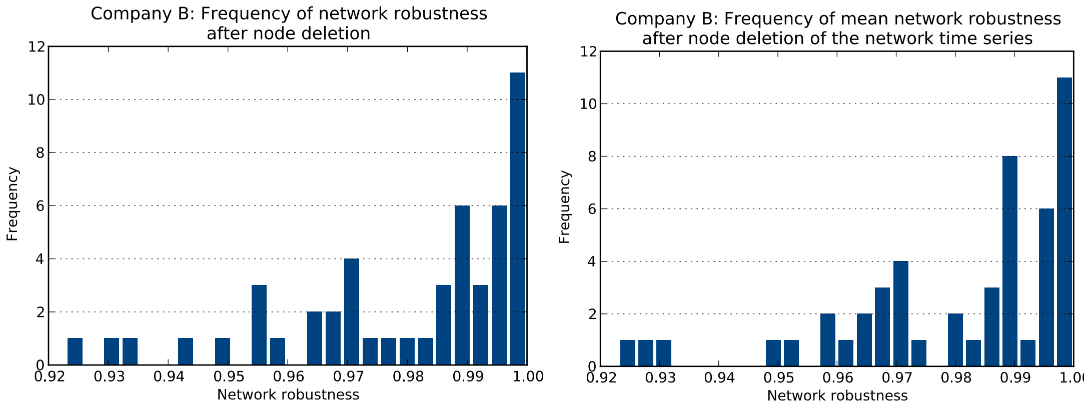

Figure 4: (a) Frequency of robustness against node deletions for all nodes. (b) Frequency of mean robustness against node deletions for all nodes for all dynamic networks over time.

If we take a closer look at the development of the robustness indicator over time, we can see that the network consist of nodes that have less influence on the robustness of the manufacturing network as well as of nodes that have a higher impact on the robustness. However, this influence is not always static. Figure 5 shows the development of the robustness against node deletion for two selected nodes for company B (Figure 4a) and company D (Figure 4b). The node that causes a high variance in robustness passes through different states of robustness (see the black line indicating the moving average), either higher or lower than the robustness value of the static network (dashed line). In contrast, the highly fluctuating robustness of the selected node in company D is much less distinct.

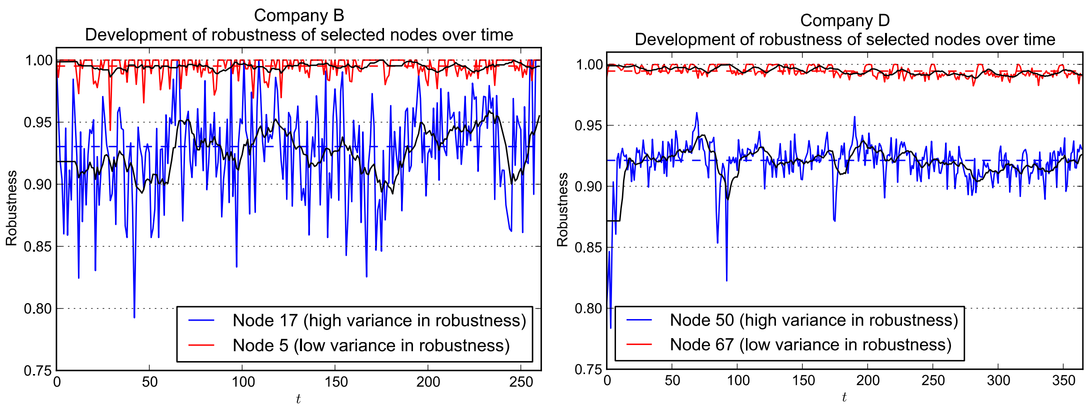

Figure 5: The development of the robustness indicator against the deletion of a selected node varies over time with the dynamic variation of the manufacturing network. (a) Node 5 in company B has less impact on the network's operations, while the robustness against deletion of node 17 fluctuates heavily. The black lines depict the 10-day moving average and the dashed lines depict the corresponding robustness value of the static network. If we observe the moving average of node 17, we see that the robustness value is clearly above or below the static value for longer periods in time. (b) For company D, the robustness fluctuations are significantly lower.

With respect to our last question, we can now state that the robustness of a manufacturing network subject to the deletion of network parts (i.e. work stations) varies over time. If we compare the robustness indicator from the static view on the network and from the dynamic view on the network, it is apparent that the influence of a single node on robustness can vary over time. However, this is not necessarily the case – depending on the individual manufacturing system, the variation of the influence of single nodes on robustness can be low, so that robustness in the corresponding static and dynamic networks is almost equal.

7. Conclusion

Manufacturing systems have been recognized as complex networks of material flow. We have taken this modeling approach and added a dynamic component by slicing the network representation into equally sized time bins. We found that, specifically for manufacturing systems, there is a distinct behavior of material flows over time. The intensity of the differences over time depends on the manufacturing system itself as well as on the selection of the time scale. Our case study has demonstrated that a time scale of one day reveals this distinctness.

With regard to robustness, we were able to show that the consideration of static, aggregated network data can result in misleading conclusions about the influence of parts of the network on robustness. We introduced a robustness indicator, which depicts the robustness of a manufacturing network against deletion of selected nodes. If this measure is applied as a function over time to the dynamic network representation of a manufacturing system, it is able to reveal in which periods the breakdown of a node threatens the performance of the manufacturing system to a greater or lesser extent.

This means that if manufacturing system characteristics such as robustness are gathered, it is necessary to check whether the system changes dynamically over time and to take this development into consideration. We expect that the same applies to other manufacturing systems characteristics, especially if the system shows a high degree of dynamic behavior in general.

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