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# Resource Scalability in Networked Manufacturing System: Social Network Analysis Based Approach

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Vijaya Kumar Manupati, Goran Putnik, and Manoj Kumar Tiwari

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## Abstract

This paper seeks to address an approach called the social network analysis method (SNAM) to evaluate the effect of resource scalability on networked manufacturing system. Considering the case of networked manufacturing mode, we have proposed a framework of SNAM for generating the collaborative networks. The collaborative networks have been obtained by transferring the input data in the form of an affiliation matrix to the UCINET and Netdraw software packages. Subsequently, we have conducted various tests to analyze the collaborative networks for finding the network structure, size, complexity and its functional properties. In this paper, a social network based greedy k-plex

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V.K. Manupati • M.K. Tiwari (✉)

Department of Industrial and Systems Engineering, Indian Institute of Technology Kharagpur, Kharagpur, West Bengal, India

e-mail: [manupativijay@gmail.com](mailto:manupativijay@gmail.com); [mkt09@hotmail.com](mailto:mkt09@hotmail.com)

G. Putnik

Department of Production and Systems Engineering, University of Minho, Guimarães, Portugal

e-mail: [nikgd@dps.uminho.pt](mailto:nikgd@dps.uminho.pt)

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algorithm has been applied to evaluate the scalability effect on different data sets of networked manufacturing system. Experimental studies have been conducted and comparisons have been made to demonstrate the efficiency of the proposed approach.

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## Introduction

Recently scalability in a manufacturing system is considered as an area of research for enhancing the techniques and methodologies to meet the challenges of the emerging manufacturing paradigm. In other words, manufacturing systems scalability can further enhance the manufacturing systems operations by providing further optimization. According to the nature of the undertaken problem, we have considered scalability as “the design of a manufacturing system and its machines with adjustable structure that enable system adjustment in response to market demand changes,” (Koren 2010). However, most of the existing manufacturing organizations still exhibit rigid organizational structures and their deterministic approach cannot support the above mentioned requirements. Researchers’ attention to a large extent have been focused on an alternative to the traditional manufacturing system which can meet high flexible manufacturing operations. Several next generation manufacturing systems such as holonic manufacturing systems (Valckenaers et al. 1994), fractal factory (Okino 1993), networked manufacturing systems and bionic manufacturing systems (Ueda 1993; Liu et al. 2002) can be conceptualized as a network of elements that are adaptable to environmental changes in particular when market demand causes turbulent fluctuations. Over the past few years, many studies focused on the newly emerged manufacturing paradigm, networked manufacturing or network based manufacturing, which has the capability to achieve the requirements and functionalities of global manufacturing (Zhou et al. 2010).

Networked manufacturing encapsulates the information and knowledge from product design to manufacturing which enables resource sharing between geographically distributed enterprises to achieve competitive advantages that would be difficult to attain with an individual enterprise (Wiendahl et al. 2007). Networked manufacturing has the ability to change its production mode from make-to-stock to make-to-order. Due to the customized manufacturing environment and competition of delivery times between different manufacturing enterprises, the objective of resource scalability and its effect on the manufacturing system is becoming a critical task. Many manufacturers nowadays try to further push optimizing the performance of the manufacturing system by implementing the scalability function. Different issues related to scalability and its relationship with some of the critical features of recent manufacturing systems are adaptability, flexibility, reconfigurability, etc. (Putnik et al. 2013). A detailed literature review on scalability as an area of research on manufacturing systems is detailed in (Wasserman 1994).

Although many approaches and models have been developed in the recent past, we have identified that there is still a need to address some more issues particularly relevant to the networked manufacturing systems. First, in networked manufacturing systems (NMS) the structure of the network does not affect the performance of the manufacturing system. In other words, the network structure has no influence on analyzing the performance of the manufacturing system. With the obtained networks from social network analysis method (SNAM) on manufacturing systems, there is a possibility to analyze the scalability and its performance on the manufacturing system (Newman 2002). Second, in NMS, the size, scope, and complexity of the network are not defined. On the contrary, with the SNAM on NMS, there is a possibility to define the network size and its functional properties such as centrality measures and network complexity in a much better way (Mendes et al. 2004). Moreover, there is hardly any information regarding the communication flow inside the network structure and the descriptive statistics that can be used to extract some information about the speed/nature of the structure. Various types of topologies and how these topologies affect the search space for exploiting the desired solution is discussed in (Neukum and Ivanov 1994). In their work, authors have presented the descriptive statistics such as average distance, diameter, and distribution sequence of various topologies and found that the series of statistics directly affects the performance of the topologies.

However, much work has been done on a wide range of problems ranging from natural phenomena to military (Lu and Hamilton 1991; Crovella and Bestavros 1996; Roberts and Turcotte 1998; Zhang et al. 2013). A framework to predict the missing quality of service values of the manufacturing services by combining social network and collaborative filtering techniques is presented (Newman and Park 2003). However, there is limited work that has applied a social network kind of analysis on manufacturing problems, in particular NM-problems. In order to give voice to the challenge, in this paper we have analyzed the existing NMS with social network method (SNM) to find the reconfiguration effect of various performance measures of the system. The detailed description of the analysis, method, and framework is presented in later sections.

Since efficiency is a significant part of networked manufacturing problems, the proposed methodology and its characteristics better serves the existing traditional networked manufacturing approach in many ways. The fundamental difference between social networks and non-social networked systems with two important properties are discussed in (Newman 2005). First, the degrees of adjacent vertices in networks are positively correlated in social networks but negatively correlated in most other networks (Watts and Strogatz 1998). Second, high levels of clustering are possible with social networks, whereas in many non-social networks clustering would be expected on the basis of pure chance (Heddaya 2002). In this paper, a case in the context of networked manufacturing is taken. Later, we have shown how a manufacturing execution system data can be extracted and viewed as a network connected with a number of nodes. Later, we map the attributes of the manufacturing system as elements of connecting nodes and the connections between the elements act as interactions where the actual material flows on different resources. Moreover, a framework has been developed and a social network analysis method

has been conducted to find the effect of resource scalability and its effect on networked manufacturing system.

The remainder of this paper is organized as follows. In section “[Problem Description](#),” we give a detailed description of a case with the basic assumptions. In section “[Framework of the Proposed SNAM Approach](#),” we presented a framework and the logical steps of the execution of a case with proposed SNM. The detailed SNAM to find the functional properties of the network has been discussed in section “[Social Network Analysis Model](#).” The scalability feature to the networked manufacturing system has been introduced and with the help of clique based social network algorithm the time scale has been measured and its results are presented in section “[Scalability with Social Network Analysis Algorithm](#).” The paper concludes with section “[Conclusion and Future Work](#)” which suggests the directions of the future work.

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## Case Study

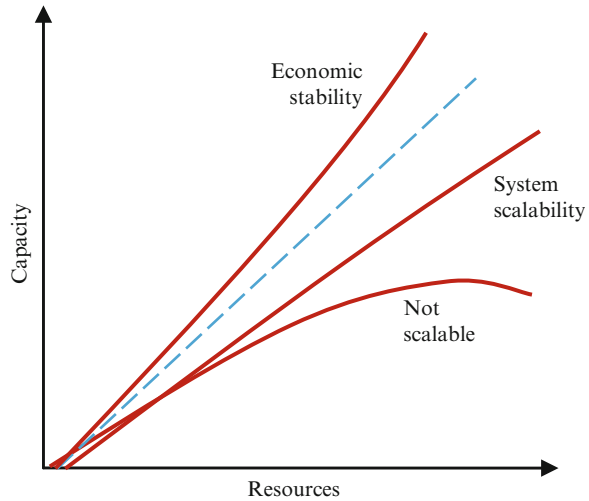
We consider a customized manufacturing environment where different customers order multiple products and it is denoted as  $n$ . Each product corresponds to a different sequence of operation steps and set of alternative process plans. Consequently, the products with alternative process plans constitute different operations which are to be processed on a set of alternative machines. However, in networked manufacturing environment, the machines with different capabilities are distributed geographically to perform various operations of the products. Hence, the transportation time between the two corresponding machines take part as a significant role for assignment of machines to production tasks. Due to alternative process plans, machines, and operations sequences the problem is much more complex and it is considered as a challenging problem in today’s manufacturing environment. As part of our objective in this paper, network size, scalability, and modularity are considered as one such performance measure to conduct SNAM to find the effect of resource scalability on the above mentioned networked manufacturing system. The above mentioned problem makes several assumptions that are worth highlighting. (a) Products preemption is not allowed; (b) The operation of a product on a machine should not be interrupted until it is finished; (c) We have considered the transportation time between the machines. With this kind of manufacturing system, after an immediate completion of the operation of a job on a machine it is immediately transported to the succeeding machine for its process. (d) A machine can handle only one product at a time. (e) All machines, products with operations and process plans are simultaneously available at time zero.

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## Framework of the Proposed SNAM Approach

It is evident from the literature that not much work has been done on finding the scalability issues in networked manufacturing systems particularly by considering SNAM. In order to respond to the aforementioned issues, it is necessary to conduct

**Fig. 1** Scalability with respect to resource and capacity (Heddaya 2002)



further optimization for economic stability. From Fig. 1 the details of scalability and its influence in relation with capacity and resources on system behavior are shown. The X-axis in the graph represents resources and Y-axis represents capacity, where resources and capacity increase the graph follows a straight line which means the mentioned performance measures are linearly increasing.

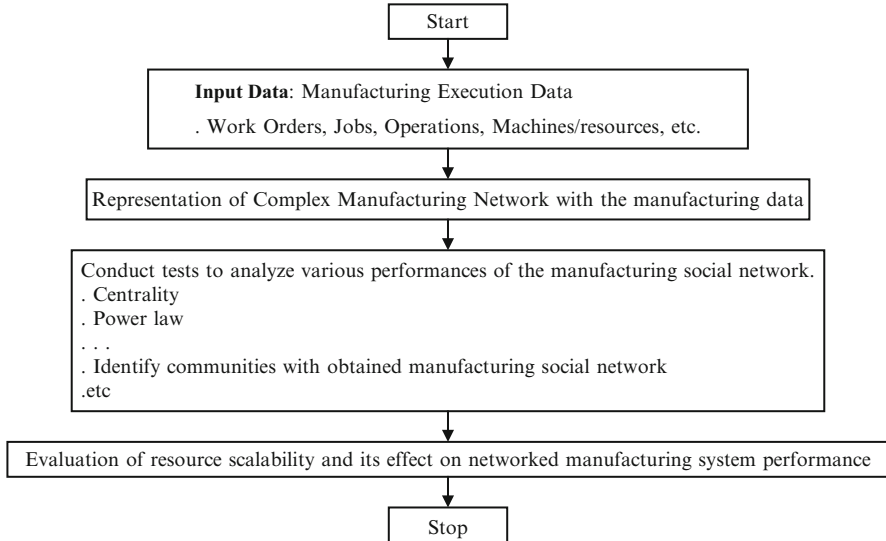
In this paper, we try to prove the system stability with the help of a case by increasing the resource scalability. Moreover, we try to find the linear pattern by increasing the resources scalability to find the effectiveness of the proposed SNAM model. In the study, we propose a step by step process of SNAM and its implementation on a networked manufacturing problem with a framework as illustrated in Fig. 2. The flowchart has been divided into three steps: (1) network modeling, (2) social network analysis method, and (3) evaluation of manufacturing system by considering.

Details of the collected data and the description of the method steps are elaborated in the following sections.

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## Social Network Analysis Model

The method shows, how the manufacturing execution data can be extracted and viewed as a network with nodes. However, it is very difficult to get the real world data of process planning and scheduling problem. Therefore, we have used input data from (Zhou et al. 2010) for conducting various tests with SNAM to obtain different characteristics of the network. The SNAM is categorized into two steps: (a) network modeling, and (b) network analysis. The detailed description of these two steps is mentioned in the following sections.



**Fig. 2** Framework to find the resource scalability effect on networked manufacturing system

## Network Modeling

A network consists of a set of nodes connected with ties indicating interaction (Newman 2005). This section presents how the manufacturing system execution data can be conceived as networks. The collected data from the literature is listed as an affiliation matrix, whose rows and columns represent the attribute (machines, jobs, operations, alternative process plans) information. The detailed case and its description is shown in Table 1.

Later, the matrix is analyzed using the modeling algorithm in the Ucinet software package and for visualizing, the obtained results are submitted to the Netdraw software package. The obtained network from the affiliation matrix is called a collaboration network. This collaboration network is more interesting and meaningful than the simple network in terms of its characteristics, size, etc. The above procedure has been repeated for the remaining scenarios and obtained different collaboration networks. The collaborative network and its details are depicted in Fig. 3.

The nodes in the network represent different attributes of the manufacturing system and for distinguishing each attribute we mentioned nodes with different colors. For example, in Fig. 3 the nodes with blue color indicate different operations, and the red-accent color indicates different machines participating in performing the task. We showed each different job node with a different color. Before analyzing the network, there is a need to run some preliminary analysis to describe the overall nature of the network. As part of that, we map the network with the elements in the manufacturing system. The detailed description of the preliminary and the detailed statistical analysis of the obtained networks are specified in the following section.

**Table 1** Input data for the 6 × 6 problem (Zhou et al. 2010)

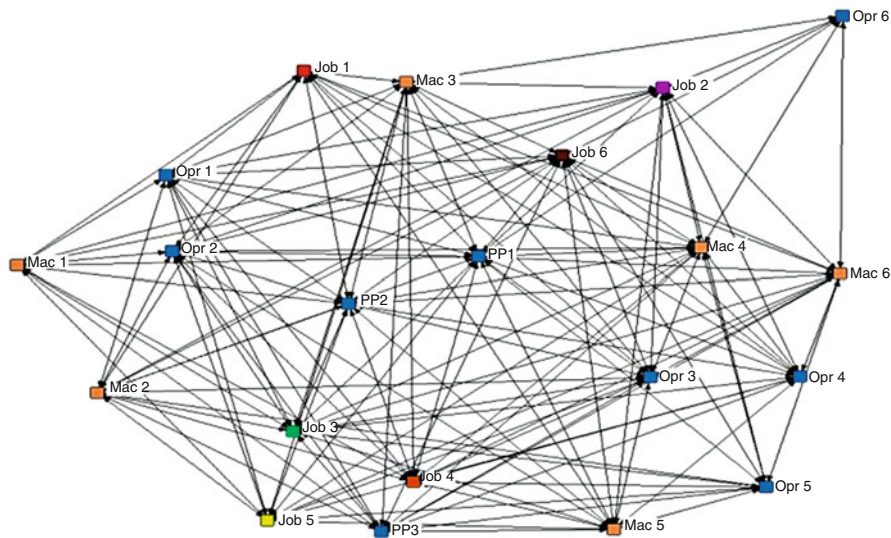
Job	PP	O1	O2	O3	O4	O5	O6
J1	PP1,1	{1, 2}	{3, 4, 5}	{6}			
		[6, 5]	[7, 6, 6]	[8]			
	PP1,2	{1, 3}	{2, 4}	{3, 5}	{4, 5, 6}		
		[4, 5]	[4, 5]	[5, 6]	[5, 5, 4]		
J2	PP2,1	{2}	{1, 3}	{2, 4, 6}	{3, 5}	{2, 4}	{4, 6}
		[4]	[2, 3]	[4, 3, 5]	[2, 4]	[3, 4]	[3, 5]
J3	PP3,1	{2, 3}	{1, 4}	{2, 5}	{3, 6}		
		[5, 6]	[6, 5]	[5, 6]	[6, 5]		
	PP3,2	{1}	{3, 4}	{5}			
		[9]	[8, 8]	[9]			
	PP3,3	{2, 3}	{4}	{3, 5}	{4, 6}	{2, 4}	
		[7, 6]	[7]	[4, 6]	[5, 5]	[6, 4]	
J4	PP4,1	{1, 2}	{3, 4}	{6}			
		[7, 8]	[7, 6]	[9]			
	PP4,2	{1, 3}	{2}	{3, 4}	{5, 6}		
		[4, 3]	[4]	[4, 5]	[3, 5]		
J5	PP5,1	{1}	{2, 4}	{3}	{5}	{4, 6}	
		[3]	[4, 5]	[4]	[3]	[5, 4]	
	PP5,2	{2, 4}	{5}	{3, 6}			
		[5, 6]	[7]	[9, 8]			
J6	PP6,1	{1, 2}	{3, 4}	{2, 5}	{3}	{4, 5}	{3, 6}
		[3, 4]	[4, 3]	[5, 3]	[4]	[4, 6]	[5, 4]
	PP6,2	{1, 3}	{2, 3}	{2, 4}	{6}		
		[4, 4]	[5, 6]	[6, 7]	[7]		
	PP6,3	{1, 2, 3}	{4, 5}	{3, 6}			
		[3, 5, 8]	[7, 10]	[9, 9]			

### Network Analysis

The goal of the network analysis is to reveal the information of the structure of the collaboration networks for potential synergies. In order to obtain the information of the structure, important properties of descriptive statistics such as average distance, diameter, and modularity of different networks have been tested. Moreover, with the probability distribution the size and complexity of the network has been identified.

### Distance of a Network

In this paper, we have submitted the input data to the Ucinet and then obtained the results of average distance for different sets. Based on properties of the network and their descriptive statistics, i.e., average distance, it is clear that the graph structure and its complexity increases with an increase in resources. In Table 2 below, the measures of average distance for different scenarios is shown, which depend on the



**Fig. 3** Collaborative networks of 6 by 6 problem

**Table 2** Scenarios used in the study and the associated graph statistics

Data	Average distance
6 by 6	1.343
6 by 10	1.353
6 by 14	1.417
6 by 18	1.475
6 by 22	1.512
6 by 26	1.554
6 by 30	1.598
6 by 34	1.624

information about the structure and the speed of communication flow. The average distance measures the average number of edges between any two nodes where the average number of cycles of influence is needed to broadcast information throughout the graph.

**Complexity Analysis**

Once a network is generated, it can be proven to be complex if the connections between the work systems follow a well known power law distribution. In this section, the mathematics behind the power law distribution and its implementation to the obtained network has been presented.

The probability distribution function for a normalized degree centrality of the collaborative networks follows power law and it is represented in Eq. 1.

$$p(x) = Cx^{-\alpha} \tag{1}$$



Where,  $C$  is constant and  $\alpha$  is an exponent and the value of  $\alpha$  is assumed as zero with  $\alpha > 0$ . We observe that while  $x$  approaches zero, the probability of  $x$  diverges. Hence, there must be some lowest value at which the power law function should be obeyed. From the descriptive statistics the value of  $x_{\min}$  is found for normalization. Normalizing the constant  $C$  and its solution in Eq. 1 gives:

$$1 = \int_{x_{\min}}^{\infty} p(x)dx = C \int_{x_{\min}}^{\infty} x^{-\alpha} dx = \frac{C}{1-\alpha} [x^{-\alpha+1}]_{x_{\min}}^{\infty} \tag{2}$$

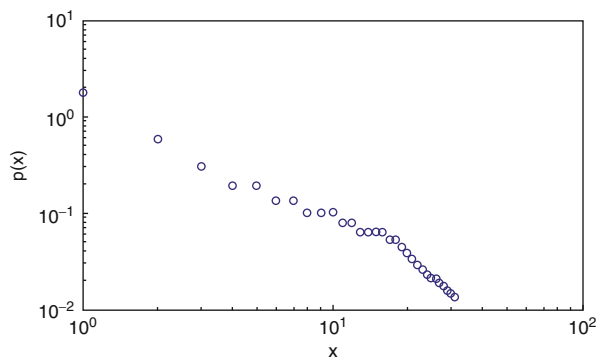
$$C = (\alpha - 1)x_{\min}^{\alpha-1} \tag{3}$$

$$p(x) = \frac{\alpha - 1}{x_{\min}} \left(\frac{x}{x_{\min}}\right)^{-\alpha} \tag{4}$$

$$\alpha = 1 + n \left[ \sum_{i=1}^n \frac{x_i}{x_{\min}} \right]^{-1} \tag{5}$$

In Eq. 2, we can observe that the value of  $x$  changes to  $x_{\min}$  with  $\alpha > 1$ , otherwise the right side of the equation would diverge. If the value of  $\alpha > 1$ , then Eq. 2 gives Eq. 3. Thus the correct normalized expression of power law is represented in Eq. 4 and we have plotted the power law distribution  $p(x)$  in a log-log graph with the exponent  $\alpha$  with the quantities  $x_i, i = 1 \dots n$  are the observed values of parameters  $x$  and  $x_{\min}$ .

Figure 4 shows, the log-log plots of different data sets with normalized distribution of the connections strength, i.e., the number of connections the nodes occurs. From the plots it is evident that the distribution obeys the power law having observed exponents of  $\alpha = 1.628$  to 1.855 for 6 by 6 to 6 by 35 of all data sets. For in-depth analysis of the power law distribution one can refer to (Newman 2005).



**Fig. 4** Power law distribution of 6 by 6 with 1.628

**Table 3** Comparison of different scenarios and their different performance measures

Data	Average distance	Size of the network (power law)	Scalability (greedy K-plex (clique) algorithm)	Modularity
6 by 6	1.343	1.628	Scalable	0.007
6 by 10	1.353	1.670	Scalable	0.008
6 by 14	1.417	1.691	Scalable	0.022
6 by 18	1.475	1.712	Scalable	0.058
6 by 22	1.512	1.731	Scalable	0.076
6 by 26	1.554	1.743	Scalable	0.084
6 by 30	1.598	1.823	Scalable	0.102
6 by 34	1.624	1.855	Scalable	0.122

## Scalability with Social Network Analysis Algorithm

The proposed SNAM is implemented with a case that is expressed with different manufacturing scenarios. Different tests were performed on several graph sizes and data sets, by fixing the number of multiple jobs to six and by increasing the number of resources to each data set.

Table 3 shows the different performances of generated collaborative graphs, whose size complexity increases with the increase in resource scalability. In this work, we try to find the increase in number of cliques according to size of the graph. Thereby, we use social network based greedy k-plex algorithm to find the scalability with respect to time complexity. From Table 3, column 4, it is clear that the number of cliques increases rapidly with the size of the graph and thereby the time complexity, i.e.,  $O(n)$  to execute the graph also increases. An algorithm for detecting community structure of social networks based on priority knowledge and modularity is used. Column 5 in Table 3 clearly depicts the increase in modularity with increase of resources in the data.

## Summary and Future Work

The paper presents a social network analysis method (SNAM) that can evaluate the effect of resource scalability in the context of a networked manufacturing system. To prove the effectiveness of the proposed method we have described a case with various complex scenarios. More importantly, we have defined a conceptual model with the help of a framework that fulfills the desired objective. In particular, solutions to queries involving SNAM such as “How can the collaborative networks be acquired from the manufacturing execution data?”, “How can the size of the network and its functional properties be extracted?”, and “How can the extracted properties influence the behavior of the network?” are provided.

To implement the above proposed method, first the manufacturing execution data has to be converted into an affiliation matrix to be inputted to the UCINET software package. Later, with the obtained results, the Netdraw software package has been used to generate the collaborative networks. It is critical to conduct various tests such as scalability tests and complexity analysis on the network to identify the characteristics, nature, and size of the collaborative network. Moreover, we have mapped the structure of the network with the attributes in the manufacturing system. Essentially, with different experimental settings, the effect of resource scalability on a networked manufacturing system has been tested on different performance measures. To validate the role of scalability and to find the effectiveness of the proposed methodology we used a social network based greedy algorithm to see whether different scenarios follow the same pattern. Results from Table 3 clearly show as the resources increase, the size, complexity, and modularity of the graph increase, thus following a linear increment in time complexity.

In future work, one can find the gain in performance measures that can be achieved with resource scalability. Moreover, some issues which are critical for manufacturing system designs such as cost of sharing resources (contention), diminishing returns at higher loads (saturation), and negative return on investment (coherency delays) can be identified with the proposed method.

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