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Discovering autonomous structures within complex networks of work systems

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ABSTRACT

Modern theories propose autonomous structures as building blocks of next-generation manufacturing systems. However, their size and scope are not agreed upon and remain a subject of research. The paper presents a method for discovering autonomous structures within existing manufacturing systems. Firstly, it is shown how a complex network model of a manufacturing system can be obtained. Then, a method for discovering structure in complex networks is applied in order to find cohesive subnetworks – candidates for the formation of autonomous work systems. The approach is illustrated in a case study of engineer-to-order production.

1. Introduction

In today's turbulent competitive environment, manufacturing systems' agility, flexibility, and adaptability are key requirements for success. However, most manufacturing companies still exhibit rigid organisational structures with highly centralised control. As an alternative, autonomous control has been suggested by numerous authors, who hypothesise that autonomy leads to better control of the system's emergent properties. Furthermore, better complexity management achieved this way leads to better system performance in highly dynamic environments [1].

The idea of autonomously controlled subsystems has existed since the 1970s, when promising results were obtained in large-scale experiments in the Swedish automotive industry. In the case of Saab, 600 workers were organised into autonomous teams, which led to an increase in productivity and quality, a decrease in machine breakdowns, a decrease in costs, and positive social effects [2].

Although success in automotive industry was short-lived because of the nature of serial production, recent manufacturing trends [3] such as decreasing lot sizes and personalisation of products have led researchers to revisit these ideas.

Modern approaches such as holonic manufacturing systems [4], autonomous work systems [5], and bionic manufacturing systems [6] all conceive of the production environment as a network of autonomous elements, working together through mechanisms of coordination and cooperation. However, the size and scope of autonomous structures are not agreed upon and remain a subject of research. Should the basic autonomous manufacturing unit be a workshop, a group of work systems working together on the same product, a manufacturing cell, or a single work system? Moreover, on what basis should autonomous units be formed? These issues are particularly relevant in one-of-a-kind and engineer-to-order (ETO) types of production where orders arrive randomly and with almost no repetitions.

The paper addresses these questions from the perspective of complex networks theory. The theory allows us to reconsider the issues of complexity and autonomy in order to find a better way of structuring a manufacturing system as a network of autonomous work subsystems. If a subsystem is to be autonomous, it must have the ability to self-organise. In a self-organising system, the information flow within the system must exceed the one between the subsystem and its surroundings. If this is to be true, elements of the subsystem must be strongly connected in comparison to their connections with external elements. On this foundation, we assume that it is possible to identify autonomous subsystems with complex network analysis.

The paper shows how a manufacturing system can be viewed as a complex network of elementary work systems, and how this network can be extracted from the manufacturing execution system (MES) data. Autonomous structures are then sought through clique percolation (CPM) [7], a social network analysis method. Identified sub-networks are used to guide an expert through the process of autonomous work system formation.

An industrial case study of ETO production is presented. The results show that existing as well as new autonomous structures are identified and suggest that the approach could be used to improve factory structure and layout as well as organisation of location-independent work such as manual welding of large workpieces or construction site assembly and installation.

2. Discovering autonomous structures in complex networks

The method of identifying autonomous structure candidates is divided into three steps: (1) network modelling, (2) network analysis, and (3) community detection, as shown in Fig. 1.

Data is acquired by an MES system and saved into a database. Routing data is extracted for the network modelling step. Network topology is analysed from the complexity perspective. Communities within the network are detected using CPM, which outputs

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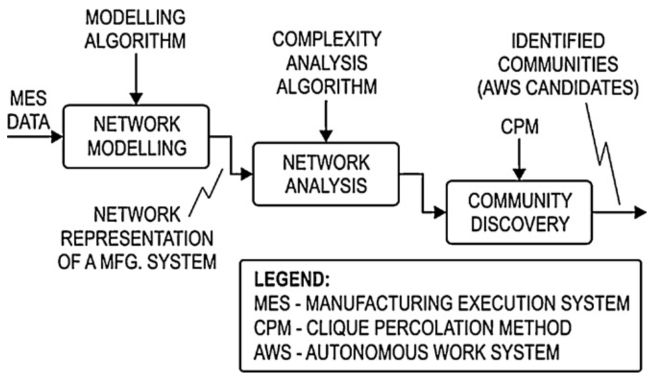

Fig. 1. Autonomous structures identification method.

tightly connected subnetworks. These, in turn, represent candidates for autonomous work systems.

Method steps are described in detail in the following sections.

2.1. Network modelling

Complex networks are graphs with non-trivial topological features; they display patterns of connectivity between their elements that are neither purely regular nor purely random. Typically, the values of the associated variables span over several orders of magnitude, their distribution conforming to a power law. For example, the number of citations for scientific papers ranges from 0 to $\sim 10^4$ [8]. Such networks describe a wide range of natural, social, and engineered phenomena, ranging from the Internet, social networks and biological systems to air traffic control amongst others [8].

It is apparent that manufacturing systems can be conceived as networks. Workpieces travel from work system to work system until they are transformed into products, creating connections between work systems – the nodes of the network. Such a representation offers an objective view of the work process, regardless of the layout or functional similarities between individual work systems. Furthermore, the underlying data can be acquired directly from the MES.

We hypothesise that work systems are connected through sequential occurrence in the same work orders. If two work systems often work together, they are strongly connected. Conversely, if two work systems never work on the same work orders, no connection exists between them. For example, sand blasting often precedes painting, but is rarely connected to weld quality control.

The hypothesis that a thusly created network is complex is supported by the nature of ETO manufacturing. Key machine tools exhibit high utilisation and have high network centrality. On the other hand, numerous machines have low utilisation, as they are only used for specific operations. This contributes to a wide range of connection strengths.

The mechanism that generates topological complexity in manufacturing environment is different from the most prevalent one, the Yule process [8]. Often termed 'preferential attachment', Yule process states that new nodes have a greater probability to attach themselves to nodes with a higher degree. In manufacturing environments, occurrence of new nodes, such as new machine tools, is uncommon. This implies that network complexity is an emergent property, arising from the internal self-organisation of the system.

The information needed to represent the manufacturing system as a network is readily extractable from MES data. The actual routing information is, in general, extractable from work order information, stored in the form shown in Table 1.

Each work order consists of a number of sequentially performed, uniquely identified operations. A confirmation ID defines the order of operations within a work order. Each operation

Table 1
Typical definition of routing information in MES data.

Work order ID	Confirmation ID	Operation ID	Work system	...
1150622	40	1049367	Markout	
1150622	50	1049368	Welding	
1150622	60	1049369	Locksmith	
1150622	70	1049370	Grinding	
1150622	80	1049371	Quality control	
1150622	90	1049372	Locksmith	
1150872	10	1051564	Sawing S	
1150872	20	1051565	Turning S	

is associated with a work system where the operation is to take place.

Based on this data, the actual material flow connecting work systems can be observed. In turn, a weighted graph can be constructed wherein connections between work systems are weighed proportionally to the number of connection occurrences.

Once a network is generated, it can be proven to be complex if the distribution of connections between work systems adheres to a power law, as explained in the following section.

2.2. Network analysis

This section presents the mathematics of scale-free networks, a subset of complex networks, which we propose as a model for complex manufacturing environments such as the engineering-to-order environment. Scale-free networks are uniquely characterised by power laws, which makes it easy to verify whether the network under observation is scale-free and therefore complex.

The probability distribution of node degrees in complex networks follows a power law (Eq. (1)):

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

where C is constant, and α is the exponent. Such networks are said to be scale-free, as the distribution is the same regardless of the scale of observation, except for an overall multiplicative constant. In such networks, nodes with highest degrees are called 'hubs'.

Fig. 2 shows an example of a random network wherein the elements are connected according to a uniform probability distribution, and a scale-free complex network generated through the Barabási–Albert model [9] which produces a power law distribution. Clearly, hubs emerge in the second case.

The exponent α in the power law distribution (Eq. (1)) is assumed to be positive. In this case, $p(x)$ diverges as x approaches 0. In real systems, power law can therefore only hold from a minimum number $x_{\min}$ onwards. With these assumptions, Eq. (1) can be normalised as follows (Eq. (2)).

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

The solution for C of Eq. (2) converges only if $\alpha > 1$. C can then be calculated according to Eq. (3).

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

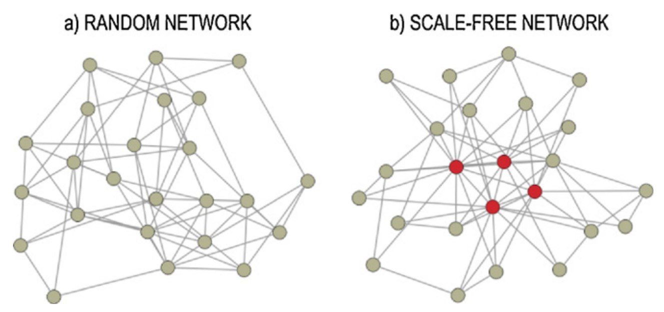

Fig. 2. Comparison of (a) random and (b) scale-free networks (both with 24 nodes and 66 edges). Nodes with degree ≥ 10 are highlighted.