Industrial Plant Layout Analyzing Based on SNA

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Abstract. Social network analysis (SNA) is a widely studied research topics, which has been increasingly being applied for solving different kind of problems, including industrial manufacturing ones. This paper focuses on the application of SNA on an industrial plant layout problem. The study aims at analyzing the importance of using SNA techniques to analyze important relations between entities in a manufacturing environment, such as jobs and resources in the context of industrial plant layout analysis. The study carried out enabled to obtain relevant results for the identification of relations among these entities for supporting to establish an appropriate plant layout for producing the jobs.

Keywords: Manufacturing systems · Plant layout · Social network analysis · Case study

1 Introduction

Social network analysis (SNA) is the mapping and measuring of relationships and flows between people, groups, organizations, computers, URLs, and other connected information/knowledge entities. The nodes in the network are the people and groups while the links show relationships or flows between the nodes [1].

The growth of interest in the techniques of social network analysis has been considerable since the 1970s and has been especially marked in the last decades [1–4]. Recent growth has been sparked partly by the increasing emphasis on the importance of "networking" in practical management guides and partly by the proliferation of "social networking" websites such as Facebook and Twitter. This has encouraged many to explore the advantages of using social network analysis [1].

In this paper is intended to analyze data through SNA, about a study for analysing the relationship between a set of jobs that incorporate a set of tasks, which have to be

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performed on a set of resources, with the aim of preparing a plant layout, by checking the influence that may exist between these entities through typical measures of SNA techniques, such as centrality, closeness and betweeness, among other descriptive statistical analysis associated that might be of relevance to be able to propose an appropriate layout for arranging the resources, according to a given production process for the jobs.

This paper is organized as follows: besides this Sect. 1 about this introduction, a brief overview about Social Network Analysis (SNA) is presented next, in Sect. 2. Section 3 presents a brief literature review about some more or less closely related work about the application of SNA techniques. Section 4 describes the case study carried out in this work for supporting the establishment of an industrial plant layout, along with the social network analysis and some important measures of network structure. Finally, in Sect. 6 are presented some conclusions and directions for future work, which are also discussed.

2 Social Network Analysis

Research on social networks has grown significantly over the last few years [5]. A social network consists of a finite set of actors and the ties between them [6]. The three basic elements in social networks are actors, ties and graphs [7]. Actors are network members that can be distinct individuals or collective units. Ties, which can be formal or informal, link actors within a network. Graphs are visual representations of networks, displaying the actors as nodes and the ties as lines [8].

Social network analysis (SNA) is the study of a social structure [9]. SNA describes a group of quantitative methods for analyzing the ties among social entities and their implications [10]. An important aspect in social network analysis is to identify key players in a network [11].

2.1 SNA Measures

The main measures considered in SNA are cohesion measures and centrality measures. Cohesion measures describe the interconnectedness of actors in a network [7]. The main measure of cohesion is the density of the network, which corresponds to the total number of ties divided by the total possible number of ties.

To calculate the density of the network Eq. 1 was used.

$$D = T/PT \tag{1}$$

Where, D, T, and PT refer to Density, Ties, and Possible Ties, respectively.

Centrality measures identify the most prominent actors, i.e. those extensively involved in relationships with other network members [11]. The most commonly used centrality measures are: degree, betweenness and closeness [12]. The centrality measures of degree, betweenness and closeness were calculated in this work through the UCINET tool.

Degree centrality is the number of actors with whom a particular actor is directly related. Betweenness centrality and closeness centrality are related to the distance (neighbourhood) between actors in a network. Betweenness centrality is the number of times an actor connects pairs of other actors [7]. Closeness centrality presents distances between actors and describes how closely actors are connected to the entire network population [13].

3 Literature Review

According to the authors in [14], Social Network Analysis (SNA) provides tools to examine relationships between people. Text Mining (TM) allows capturing the text they produce in Web 2.0 applications, for example, however it neglects their social structure.

In their paper [14] the authors apply an approach to combine the two methods named "content-based SNA". Using the R mailing lists, R-help and R-devel, they show how this combination can be used to describe people's interests and to find out if authors who have similar interests actually communicate. As stated by the authors, they found that the expected positive relationship between sharing interests and communicating gets stronger as the centrality scores of authors in the communication networks increases [14]. Moreover, they refer that the paper shows how content-based SNA can be used to find people's interests in mailing list networks.

Additionally, by comparing communication graphs and networks showing who has similar interests, a relationship between the correlation of these two and node centrality could be found. Accordingly, the authors conclude that the expected relationship between sharing interests and communicating exists only for very active authors while less active authors do not answer everyone who has similar interests. Thus, they refer that the communication efficiency can be regarded to be high for very active mailing list authors while it is moderate for middle-active authors. The paper also suggests using only the subjects to find the relationship between communicating and sharing interests because the content contains more noise [14].

Another interesting contribution is presented in [15], were a case study examines infrastructure planning in the Swiss water sector. According the authors, water supply and wastewater infrastructures are planned far into the future, usually on the basis of projections of past boundary conditions, but they affect many actors, including the population, and are expensive. Therefore, their objective consisted on investigating fragmentation in water infrastructure planning, to understand how actors from different decision levels and sectors are represented, and which interests they follow [15]. The network analysis they did obtain confirmed their hypothesis of strong fragmentation, as they sated that they found little collaboration between the water supply and wastewater sector (confirming horizontal fragmentation), and few ties between local, cantonal, and national actors (confirming vertical fragmentation). Moreover, according the authors infrastructure planning was clearly dominated by engineers and local authorities, and little importance was given to longer-term strategic objectives and integrated catchment planning, which was perceived as more important in a second analysis carried out by the authors, that went beyond typical questions of stakeholder analysis. In their study, the authors concluded that linking a stakeholder analysis, comprising rarely asked questions, with a rigorous social network analysis is very fruitful and did enable to generate complementary results. Moreover, this combination gave them deeper insights into the socio-political-engineering world of water infrastructure planning, which according their opinion is of vital importance to the general welfare [15].

As stated in [16] coordination increasingly occurs through networks of informal relations rather than channels tightly prescribed by formal reporting structures or detailed work processes. However, while organizations are moving to network forms through joint ventures, alliances, and other collaborative relationships, executives generally pay little attention to assessing and supporting informal networks within their own organizations. Moreover, the authors refer that social network analysis is a valuable means of facilitating collaboration in strategically important groups such as top leadership networks, strategic business units, new product development teams, communities of practice, joint ventures, and mergers. Moreover, according to them, by making informal networks visible, social network analysis helps managers systematically to assess and support strategically important collaboration [16].

Another interesting example of application of SNA is provided in [17], were is presented a mixed evaluation method that combines traditional sources of data with computer logs, and integrates quantitative statistics, qualitative data analysis and social network analysis in an overall interpretative approach. The authors propose the use of several computer tools to assist in this process, integrated with generic software for qualitative analysis. The authors applied their evaluation method and tools incrementally and validated them in the context of an educational and research project that had been going on during three years. The use of their proposed method was illustrated on their paper through an example consisting on the evaluation of a particular category within their project. Moreover, their proposed method and tools aimed at providing an answer to the need for innovative techniques for studying new forms of interaction emerging in Computer-Supported Collaborative Learning (CSCL); for increasing the efficiency of the traditionally demanding qualitative methods. The authors concluded that their methods can be used by teachers in curriculum-based experiences; and at the definition of a set of guidelines for bridging different data sources and analysis perspectives [17].

In paper [18], the authors provide another kind of application of SNA, for supply chain researchers with an overview of social network analysis, covering both specific concepts (such as structural holes or betweenness centrality) and the generic explanatory mechanisms that network theorists often invoke to relate network variables to outcomes of interest. As stated by the authors, one reason for discussing mechanisms is to facilitate appropriate translation and context-specific modification of concepts rather than blind copying. Therefore, they have also taken care to apply network concepts to both "hard" types of ties (e.g., materials and money flows) and "soft" types of ties (e.g., friendships and sharing of information), as according to them, both are crucial (and mutually embedded) in the supply chain context. Moreover, the authors did also aim to point to areas in other fields that they thought would be particularly suitable for supply chain management (SCM) to draw network concepts from, such as sociology, ecology, input–output research and even the study of romantic networks. According to their statement, they believe that the portability of many network concepts is high to provide a potential for unifying many fields, and a consequence of this for SCM it may enable to decrease the distance between SCM and other branches of the management science.

As we can realise through the overview presented in this section about applications of SNA, this kind of approaches and underlying techniques can be applied to many different domains, in general, and also to some more specific areas, for instance, in the context of industrial management, and in this paper the aim is its application for establishing an industrial plant layout. In this paper we are working with a computational complex problem, which therefore requires heuristic solutions as the one proposed in this paper, based on SNA analysis.

Moreover, due to the computational complexity of this kind of problems there was also a need to restrict the dimension of our case study entry data, as will be briefly described on the next section.

4 Case Study

In this study a set of 25 jobs (jobs, J1… J25), including a set of tasks, varying from 1 up to 5, have been considered to be processed on manufacturing resources, among a set of 5 available (R1,…, R5), to analyze, through the application of a SNA technique, measures of centrality, closeness and betweeness, among other relevant descriptive statistical analysis for supporting the establishment of an appropriate plant layout for producing the jobs.

In a social network analysis first a network has to be modelled. Therefore, it was created a matrix with all ties identified between the jobs and the corresponding manufacturing resources, for producing the jobs. This data is presented in the affiliation matrix expressed in Table 1 below, were 1 is assigned in cases when a given manufacturing resource processes an operation on a given job and 0 for the opposite situation. The matrix was uploaded in the software UCINET, which was the software tool used for the SNA technique execution.

After that, using the same software, the social network graph was created (Fig. 1). In this figure are represented all the ties that occurred between the different entities (jobs and manufacturing resources) for accomplishing the underlying tasks. With this social network graph it is possible to realize how many manufacturing resources the jobs interact with, and also to observe the entities that have more intense activity in this production scenario.

5 Experimentation Method Based on the Social Network Analysis

In this paper and experimentation method based on Social Network Analysis (SNAM) is proposed for enabling to describe how the manufacturing execution data can be extracted and viewed as a network with nodes. Consequently, through our considered case study the data has been extracted, and which has been analysed through various SNA tools. Finally, we did carry out a process for identifying different characteristics of the obtained

Table 1. Jobs affiliation matrix

	R1	R2	R3	R4	R5
J1	0	1	0	0	0
J2	0	0	0	1	0
J3	1	1	0	0	0
J4	0	0	1	0	0
J5	0	1	0	0	0
J6	0	1	0	1	0
J7	0	0	1	1	0
J8	1	0	0	0	1
J9	0	0	1	0	0
J10	1	1	1	1	1
J11	1	1	1	1	1
J12	0	0	0	0	0
J13	0	1	1	0	1
J14	0	0	0	0	0
J15	0	1	1	1	1
J16	1	1	0	1	1
J17	1	1	0	1	0
J18	0	1	1	0	1
J19	0	1	0	0	0
J20	0	1	1	1	0
J21	1	1	0	0	1
J22	1	0	1	1	1
J23	0	0	0	0	1
J24	0	1	1	0	1
J25	0	1	0	1	0

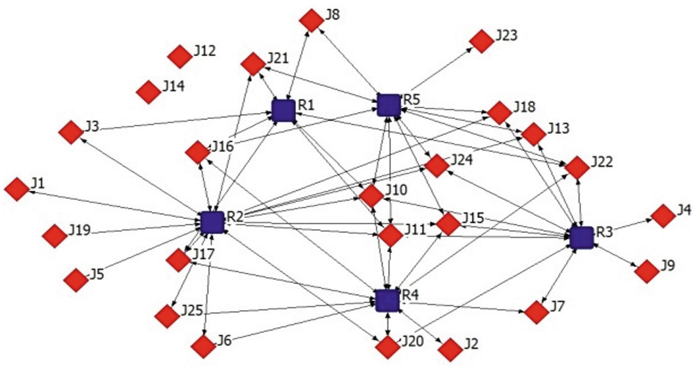

Fig. 1. Social network graph of the production scenario.

network in detail. The SNAM is categorized into two steps: (a) network modelling, and (b) network analysis as it is mentioned in the following Sects. 5.1 and 5.2.

5.1 Network Modelling

A network consists on a set of nodes connected through ties, which indicate interaction. In this section is briefly described how the manufacturing system execution data can be represented as a network. In this step we have fed the input data which is in the form of affiliation matrix into the UCINET software package. Using Net draw we have represented the matrix in the form of a collaboration network. The network is a highly expressive and meaningful way of data representation by enabling to show a variation in the representation of the resources and jobs in terms of shape, size, and colour. The considered resources are represented with a blue coloured square shape and the resources are shown as a red diamond. The arrows connecting the jobs and resources clarify that a particular resource is required to complete a given job. This collaborative network can thus be effectively used to understand which resource is highly influential and the inter relations among them. With the data that has been collected from the case study and their corresponding details through the use of three centralities, a visual interpretation is possible, as can been seen in Table 2. The relationship between the attributes (jobs and resources) is represented in Fig. 1.

5.2 Network Analysis

The main objective of network analysis is to breakdown and comprehend the complex information of the structure into collaboration networks for the extraction of potential synergies. In order to obtain the information of the structure, crucial features about descriptive statistics such as degree centrality, betweeness centrality, and closeness centrality about the network have to be considered to examine the complexity, interdependencies and interrelationships involved on it.

In this research, we have considered the three most popular centrality measures such as Freeman's degree, closeness and Freeman's betweenness centrality about each attribute. The centrality is used to find how influential a node is in the network and also the interrelations among them for its complete analysis. In the Table 2 below, values of the three centralities about the collaboration networks for the above referred scenarios regarding 5 resources and 25 jobs is presented.

The degree centrality measures influence on the node from and to its closest neighbour with complexity of O(n) to linearly scale the nodes in the network, where n is the number of nodes. The jobs and resources with higher degree centrality represent strongly connected ones, whereas the jobs and resources with lower degree centrality exhibit very less connections. Thus, we have identified the key resources which are having higher degree centrality and can act as hubs and also serve as the central elements of the industrial plant.

The other two centrality measures betweenneess and closeness give us information about the shortest path involved among the various attributes of the network.

Table 2. Centrality measures for the resources

	Degree centrality	Betweeness centrality	Closeness centrality
R2	16	142.896	27.619
R3	11	76.180	25.217
R4	11	64.360	25.217
R5	11	60.580	25.217
R1	8	24.977	23.967
J10	5	20.686	26.606
J11	5	20.686	26.606
J15	4	13.928	26.126
J16	4	10.613	25.217
J22	4	11.284	24.786
J18	3	7.478	25.217
J24	3	7.478	25.217
J13	3	7.478	25.217
J20	3	7.600	24.786
J17	3	5.292	24.370
J21	3	4.730	23.967
J3	2	1.706	23.200
J25	2	2.057	23.577
J6	2	2.057	23.577
J7	2	2.095	22.481
J8	2	0.831	21.481
J5	1	0	22.137
J1	1	0	22.137
J19	1	0	22.137
J2	1	0	20.567
J9	1	0	20.567
J23	1	0	20.567
J4	0	0	20.567
J14	0	0	0
J12	0	0	0

The betweenness centrality has the higher level of control on the information floating between different nodes in the network while the closeness centrality is a measure of how closely the nodes are connected with each other. This data can be used to analyze the order in which the resources of the plant need to be arranged and how close each resource need to be from each other.

From the above analysis we have gained complete understanding of the various relations among the resources to complete the assigned jobs effectively. The resources that are key machines as hubs of the industrial plant used for completing maximum number of jobs are identified by degree centrality. Also, the arrangement of the resources in the plant layout based on their interrelations is also understood through the betweenness and closeness centrality measures. In this way the complete industrial layout can be designed through the obtained statistical data.

6 Conclusion

This paper focused on the application of SNA on an industrial plant layout problem. The study aimed at analyzing the importance of using SNA techniques to examine important relations between entities in a manufacturing environment, such as jobs and resources in the context of industrial plant layout analysis. The study carried out enabled to obtain relevant results for the identification of relations among these entities for supporting to establish an appropriate plant layout for producing the jobs.

Future work is planned for continuing to explore the application of SNA techniques to this kind of industrial plant layout problem, for instance, by exploring this problem in the context of extended manufacturing environments, namely including a big data analysis, and also to compare the application of SNA techniques with some other existing methods for industrial plants layouts establishment and analysis.

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