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PROPOSITION OF THE USE OF NETWORK THEORY FOR DECISION MAKING ON MANUFACTURING TECHNOLOGIES

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Abstract. *The introduction of new technologies and information systems on the market allows companies to make innovative solutions for their processes and products, as well as to further develop existing ones. New technologies can contribute significantly to the results of companies if they are properly applied in the manufacturing processes. However, the increasing pace of technological development also generates doubts in the processes of choosing which technology or system to apply next. Knowing this, visual tools were developed, based on network science algorithms, as a proposal to support this decision-making process. The relations between the technologies and systems were established by combining the database of SENAI 4.0 industry maturity assessment and the Accelerating the Impact of IIoT on Small and Medium Enterprises project, idealized by the World Economic Forum. After processing the data, the responses of 1717 Brazilian companies were considered, indicating which technologies and systems they had applied among pre-defined options. Moreover, by verifying the primary data of the respondent companies, it was also possible to notice distinct characteristics of technology adoption between different sectors of the manufacturing industry. It can also be seen that the graphical visualization of networks allowed a unique analysis of technological applications, by highlighting the existing patterns found in the database. Thus, it is suggested that the network theory can be used as a tool to support decision making for the application of technologies and information systems, to spot new market opportunities, as well as to direct public policies.*

Keywords: *Network Theory, Industry 4.0, Manufacturing Technologies, Decision Making, Lean Manufacturing*

1. INTRODUCTION

Technological development is causing profound changes in the way of living and working, in addition to impacting all areas of knowledge, economies and industries (MDIC & MCTIC, 2016). The growing variety of industrial technologies available on the market represents both opportunities and challenges for entrepreneurs. The fast pace of technological development makes it possible to find process solutions and improvements for previously unsolvable problems. However, the acceptance and adoption process of new technologies is usually hampered by several factors.

It is possible to argue that one of these factors is the lack of knowledge and availability of reliable information about technological applications and their potential benefits. According to the International Business Machines Corporation - IBM (2018), approximately one in three leaders do not trust the information they have to make decisions. In general, searching for information online and consulting sellers may help in this regard. However, focusing on few technologies may be time consuming and bias decisions, due to individual search results and conversations with salespeople. Searching for reliable data sources, which may highlight market trends, technology-related best practices and case studies, typically offers greater certainty for decision making. Arguably, this data-driven mindset is the main reason for the significant growth in data demand seen in recent years. It was found that between 2016 and 2018, more than 90% of the total existing data to date was created (IBM, 2018).

However, the sheer volume of data to be organized and interpreted in order to identify relevant information can be an obstacle for organizations. It is observed that many companies face difficulties to process, analyze and use the data they are collecting. Moreover, it is suggested that if the data cannot be transformed into relevant information for decision making, they are useless (Hoelscher and Mortimer, 2018)

In this context, data visualization methods are often applied to facilitate analysis by decision makers. In general, visual tools allows us to communicate and analyze information more efficiently, and also improves the ability to make comparisons and to notice existing patterns (Few, 2013). Network theory or graph theory represents a data visualization solution with specific characteristics that can lead to new and useful insights. Generally speaking, graphs may be used to identify relevant connections, patterns and trends that exist among data, which may be imperceptible in graphics, charts or other visualization tools.

From databases that quantify applications of a set of technologies and systems, usually related to Industry 4.0 and lean manufacturing, in 1717 Brazilian companies, graphs were developed and named “technology networks”. The networks highlight which technologies are most used and their proximity to others, indicating the degree to which each pair of technologies were simultaneously applied. Thus, this article proposes to analyze the application of network theory as a decision-making tool aimed at the development of manufacturing systems. Furthermore, it is expected to verify patterns on the adoption of technologies and systems, as well as whether the results may be related to the industrial segment and the size of the companies.

2. THEORETICAL BACKGROUND

This chapter presents a simplified literature review of the main themes of this work. Initially, the theme of Industry 4.0 and its enabling technologies is presented. Then, possible relations between Industry 4.0 and lean manufacturing are discussed. Finally, some concepts and examples of the application of network theory are presented.

2.1 Industry 4.0 and its Enabling Technologies

The term “Industry 4.0” was introduced at the Hannover fair in 2011 and promptly became the focus of the government of Germany and other European countries (Ghobakhloo, 2018). At that time, the German government, universities and private companies structured a strategic program for the development of advanced production systems, aiming increasing the productivity and efficiency of German industry (Kagermann *et al*., 2013).

According to Veile *et al*. (2019), Industry 4.0 is characterized by connecting people, machines, objects and information and communication technologies (ICT) in an intelligent, horizontal and vertical way. Other authors also perceive Industry 4.0 as the integration between manufacturing operating systems and ICTs, with emphasis on the Internet of Things (IoT), thus forming cyberphysical systems (CPS) (Wang *et al*., 2015; Dalenogare *et al*., 2018). Besides CPS and IoT, the review of academic and corporate publications done by Hermann *et al*. (2015) identified also internet of services (IoS) and smart factories as key components of Industry 4.0. From this, it can be argued that Industry 4.0 focuses on the digitization of physical goods and the integration of digital systems in the value chain. Thus, the generation, analysis and communication of data acts as a fundamental basis for connecting and enabling the application of a variety of new technologies (Geissbauer *et al*., 2016).

Other government programs and initiatives have been conceived with similar concepts and objectives, but using different terms to describe them, such as the United States of America’s initiative called “smart manufacturing”, also known as “advanced manufacturing”. initiatives have as key element in their strategies, the encouragement and support for the emergence of enabling technologies (Daudt and Willcox, 2018; Veile *et al*., 2019). According to Deloitte (2015), the application of related technologies accelerates the development of individual solutions, as it provides flexibility and cost reduction in industrial processes. Moreover, it is argued that the application of digital technologies can provide shorter delivery times, improve equipment efficiency and product quality (Geissbauer *et al*., 2016).

However, not all digital technologies are considered to be enabling technologies of Industry 4.0. According to Pacchini *et al*. (2019), enabling technologies are required to provide an adequate implementation of Industry 4.0. The authors conducted a review of 19 academic and corporate publications to identify which technologies are enabling Industry 4.0. When analyzing the results, it was possible to notice an agreement on some technologies (IoT, big data and cloud), as well as that many were rarely mentioned. Thus, it is suggested that there is no single and accepted set of enabling technologies, or as Pacchini *et al*. (2019) state, “there is a significant lack of agreement among the authors”. Along these lines, Benitez *et al*. (2021) argue that there are studies that consider only disruptive technologies, such as IoT and big data, while others include classic advanced manufacturing technologies, such as robotics and automation.

Regarding technology adoption in Industry 4.0, it is worth mentioning that worse results are obtained when technologies are applied individually than when applied together (Alcácer and Cruz-Machado, 2019). Reischauer (2018) argues that the combination of technologies in integrated solutions is the main competitive advantage generated by Industry 4.0. This is because one technology can influence the performance of others, generating a greater impact by combining its effects and results. Therefore, in order to improve the performance of technologies, as well as of the assets of an organization, it is necessary to have a balanced integration between operational technologies (OT), engineering technologies (ET) and information technologies (IT) (WMF, 2018).

2.2 Lean Manufacturing in Industry 4.0

Even though the integration of enabling technologies can generate impressive results, Industry 4.0 projects often fail to achieve the desired benefits or to meet the true interests of organizations (Issa *et al*., 2018). In fact, studies indicate that productivity is the main concern in industrial sectors in emerging countries, such as Brazil (CNI, 2016), instead of flexibility, adaptability, innovation among others that are proposed by Industry 4.0 initiatives. Even knowing that this focus is limited, the Brazilian industry first focuses on increasing efficiency and then moves to applications targeted for the development of new products and business models (CNI, 2016). From this, it is proposed to address the topic of productivity, or more precisely: lean manufacturing and how it relates to Industry 4.0.

Nowadays, it is possible to notice that many companies, especially in industrial sectors, seek to apply lean manufacturing concepts, as well as the latest Industry 4.0 trends in order to remain competitive (Kolla *et al*., 2019). Regarding this effort to combine different concepts, the main possible relationships suggested in the literature are: lean as a basis for the implementation of Industry 4.0; Industry 4.0 as a way to improve lean efficiency; Industry 4.0 complements lean; the integration of enabling technologies should change lean principles (Dombrowski *et al*., 2017; Bauer *et al*., 2018).

According to Bauer *et al*. (2018), the general principles of lean will likely remain the same with the development of Industry 4.0, but its implementation can be complemented by new technologies. The authors argue that the adoption of new technologies brings customer requirements that cannot be met by manual lean methods, such as tracking products in manufacturing and delivery processes. For Prinz *et al*. (2018) Industry 4.0 is characterized by the digitization of production, and does not consist of a methodological approach, as proposed by lean. The authors argue that the two themes have fundamental differences between their approaches. However, they emphasize that both share the objective of increasing the value added.

Besides the similarities found in concepts and goals of Industry 4.0 and lean, it is also possible to verify interactions among their tools, methods and technologies. Examples of this can be: the optimization of value stream mapping (MFV) processes by reading bar codes in material handling or transport processes, in order to automatically identify optimal paths and stock levels (Bauer *et al*., 2018); the application of RFID sensors on Kanban systems, aiming to automatically recognize and inform the level of parts in replacement boxes, providing real-time information for the supply chain (Sanders *et al*., 2016; Hofmann and Rüsch, 2017).

Although there are divergent opinions on how the themes interact, it is possible to argue that there are mostly positive relationships between lean manufacturing and Industry 4.0 (Sanders *et al*., 2016). From this assumption, the method proposed in this work also seeks to map existing relationships among lean tools, systems and the enabling technologies of Industry 4.0.

2.3 Network Theory and Applications

Network theory is an interdisciplinary area that involves the mathematical formalism of graph theory and analyzes based on statistical tools (Silva, 2016). According to Santos and Kobaschi (2009), the focus of the application of these statistical principles is not only to quantify and verify data, but also to give meaning to them, so that they can be better used in science and technology policies, among other purposes.

Regarding this subject, it is important to highlight “The atlas of economic complexity” developed by Hausmann *et al*. (2011). In their study, the authors mapped all types of products being exported by countries and presented the results in a network called “the product space”. For this, Hausmann *et al*. (2011) assumed that: if two products share most of the capabilities and resources required for their production, countries that export the first are more likely to export the second. Based on this theory, the authors calculated the probability that countries have to export different products simultaneously. Then, it is assumed that countries tend to diversify into products that are near to those they already export in the product space, which was empirically demonstrated by Hidalgo *et al*. (2007). Therefore, the product space can be interpreted as an industrial map, which explicitly shows which products require similar capabilities, as well as exportation patterns and trends.

Another example of the application of network theory is “the space of technological competences”, developed by Silva (2016) based on the competences of users registered in the CORDIS (Community Research and Development Information Service) platform. The resulting network, connects similar technological competencies in terms of productive capacity. Then, based on the theory that the space of technological competences enables the visualization of ways in which competences are more easily aggregated, Silva (2016) proposed a method to identify new technological competences to be developed by Science and Technology Institutions.

Although there are studies relating Industry 4.0 with lean manufacturing concepts, technologies and tools, it was not possible to find publications containing all the search terms “Network Theory”, “Industry 4.0” and “Lean Manufacturing” in the databases of Engineering Village and Scopus. Therefore, even though other visualization methods could be used, this study focuses on the application of network theory to quantify, map and highlight the possible relationships between the subjects.

3. METHODOLOGY

In order to achieve the goals of this research, a network science algorithm was developed. The development process of the “technology network” is described in this Section, as well as research delimitations and the main criteria considered.

3.1 Data acquisition and processing

The initial and probably the most critical requirement for the development of the networks consisted in searching for databases that related the themes of Industry 4.0 and lean manufacturing. With this goal, it was proposed to use the answers from the maturity assessment of the National Service of Industrial Training - SENAI, which is an institution that offers technological services that promote innovation in the Brazilian industry, as well as data from the project "Accelerating the Impact of Industrial Internet of Things on Small and Medium Enterprises". The first consists of an online questionnaire developed based on the "Industrie 4.0 maturity index" of the German Academy of Science and Engineering - ACATECH (Schuh *et al.*, 2017). The latter is a project of the Ministry of Economy of Brazil and the Brazilian State of São Paulo, led by the Technological Research Institute - IPT, and conceived by the World Economic Forum - WEF. This project is aimed at small and medium enterprises that want to apply Industry 4.0 concepts (IPT, 2020). It also has a questionnaire for an initial assessment of companies that is similar the one of SENAI.

Both questionnaires contain three identical questions, which feature lists of production management systems (PS), operational technologies (OT) and information technologies (IT) known in the industry. The responding companies were asked to select the systems and technologies which they have applied. The acronyms and terms used to describe the technologies and systems were slightly adapted for the development of the technology networks, and are presented in Table 1 depicted below.

Table 1. Acronyms and Terms Used in the Technology Network.

Production Management Systems		Operational Technologies		Information Technologies	
Acronym	**Description**	**Acronym**	**Description**	**Acronym**	**Description**
5S	5S	3DP	3D Printing	BIG	Big Data Analytics
JIT	Just in Time	CLD	Cloud Computing	CAD	Computer-Aided Design
KAI	*Kaizen*	EBS	Embedded Systems	ERP	Enterprise Resource Planning
KAN	*Kanban* / Pulled Production	MDC	Machine Data Collection	LYS	Layout Simulation
PDCA	Plan Do Check Act	M2M	Machine to Machine Communication	MES	Manufacturing Execution System
PST	Process Standardization	PMS	Process Monitoring Sensors	PDM	Product Data Management
SMED	Single Minute Exchange of Die	RFID	Radio Frequency Identification	PLM	Product Lifecycle Management
SPD	Supplier Development	ROB	Autonomous and Collaborative Robots	PPS	Production Planning System
TPM	Total Produtivity Maintenance	RTLS	Real-Time Locating Systems	SCM	Supply Chain Management
VSM	Value Stream Mapping	SAM	Mobile Systems and Applications	SIM	Simulation of Manufacturing Processes

The total number of responses from the SENAI database was 2187, received from March 2018 to November 2020. The "Accelerating the Impact of Industrial Internet of Things on Small and Medium Enterprises" project received the responses of 110 companies submitted in 2020. Knowing that the online maturity assessment of SENAI is accessible for free, a data filtering and processing was performed. For this purpose, only responses of companies whose CNPJ, a National Registry of Legal Entities, was listed on the Brazilian Special Department of Federal Revenue website were used. Then, in order to keep only a single response per company, older responses that contained the same CNPJ were disregarded, resulting in 1717 useful responses for the development of the networks. Among these, 575 classify themselves as micro-enterprises, 545 as small, 401 as medium and 196 as large companies.

It is important to highlight that a well-accepted literature definition and description of the technologies and systems would be essential for a possible validation of the technology networks. However, this is not one of the goals of this article, since these points were previously defined to develop SENAI's maturity assessment for Industry 4.0. As aforementioned, this study seeks to use available data to visualize patterns and trends, which consists of descriptive research with a correlational design. This type of research aims not only to investigate the characteristics of a reality, but also to compare the joint occurrence of certain variables. Since this is not an experimental research, it is not expected to make strong causal inferences between the variables (Appolinário, 2006). Therefore, the generated Technology Networks are not intended to be statistically representative of the Brazilian industrial scenario or specific industrial segments.

3.2 Development of the Technology Networks

With the data filtered, the next activity consisted in calculating a proximity matrix that lists all the technologies and systems evaluated. The proximity matrix presents the conditional probabilities "$\emptyset_{C_1C_2}$" that a company which has technology "c1" applied would also have technology "c2". The calculation of proximity between two technologies is given by equation (1).

$$\emptyset_{C_1C_2} = \frac{\sum_c M_{pc_1} M_{pc_2}}{\max(U_{c_1,0}, U_{c_2,0})}, \tag{1}$$

Analogously to the equation proposed by Hausmann *et al*. (2011), equation (1) sums the number of companies that have both technologies analyzed (Mpc = 1 if company "p" has technology "c", otherwise, Mpc = 0) and divides by the highest ubiquity (Uc = total quantity of companies that have technology "c") between them. The equation predicts that the conditional probabilities are not symmetric, that is, the probabilities of having "c2", given "c1", and of having "c1", given "c2", are not equal. Therefore, the division by the maximum ubiquity value makes the process symmetrical and more rigorous (Hausmann *et al*. 2011; Silva, 2017). As a result of the equation, proximity values are real numbers equal or greater than zero, and equal or less than one.

The proximity matrix is the main data input needed for the programming of the network algorithm. It was developed with the RStudio software and the igraph library, which aims to create and manipulate graphs (Csárdi and Nepusz, 2006). To facilitate the interpretation of the results, different colors were adopted for the three areas of technologies and systems (PS, OT and IT), as well as vector sizes were made proportional to the ubiquities found. Furthermore, the results of proximity between technologies are highlighted by the width and gray scale of the edges that connect them. Besides, proximity values smaller than 0.3 (or 30%) were disregarded for visualization purposes. Figure 1 below shows the initial version of the technology network, which presents a fuzzy aspect.

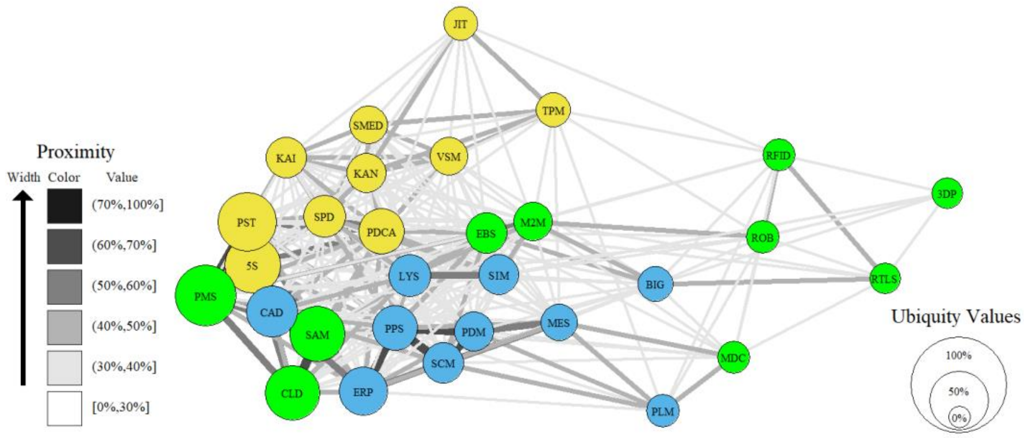

Figure 1. Initial Version of the Technology Network.

It can be seen that the three areas of technologies and systems (PS, OT and IT) naturally form clusters in the initial version of the network. Nonetheless, it is difficult to visualize all connections among the vectors, even disregarding proximity values less than 0.3. This issue leaded to a new criterion for highlighting only the main relationships between technologies and systems of different areas. For such cases, proximity values less than 0.5 were also disregarded. With this change, it is still possible to observe the most important results of simultaneous application between technologies from different areas. The final version of the technology network is presented in the following Section.

4. RESULTS AND DISCUSSION

The main idea behind the application of the technology network to support decision making is highlighting application patterns between the technologies and systems. In this sense, similarly to the studies of Hausmann (2011) and Silva (2017), it is possible to assume that new technologies are more easily implemented when combined with existing ones. It is suggested that their respective positioning and proximity in the networks may reflect similarities in investments, knowledge, processes, objectives, among other factors related to their applications. The final version of the technology network considering the technological applications of the 1717 Brazilian companies is presented in Figure 2.

The technology network presents some specific results that can generate useful insights regarding the adoption process. As can be seen, 5S and process standardization (PST) have major roles for the production management systems, not only as a basis for starting the implementation of other lean tools, but also for some technologies. On the operational technologies side, process monitoring sensors (PMS), mobile systems and applications (SAM) and cloud computing

(CLD) have this similar role and share high proximity values, which indicates that they are usually applied together. In a way, these technologies complement each other (collecting data, transmitting it to mobile applications and storing in the cloud), which is aligned with Industry 4.0 concepts and the previously mentioned argument that combining technologies improves their performance. Finally, CAD is the only bridge connecting information technologies to other areas, which may be a consequence of its major relevance for certain industrial segments.

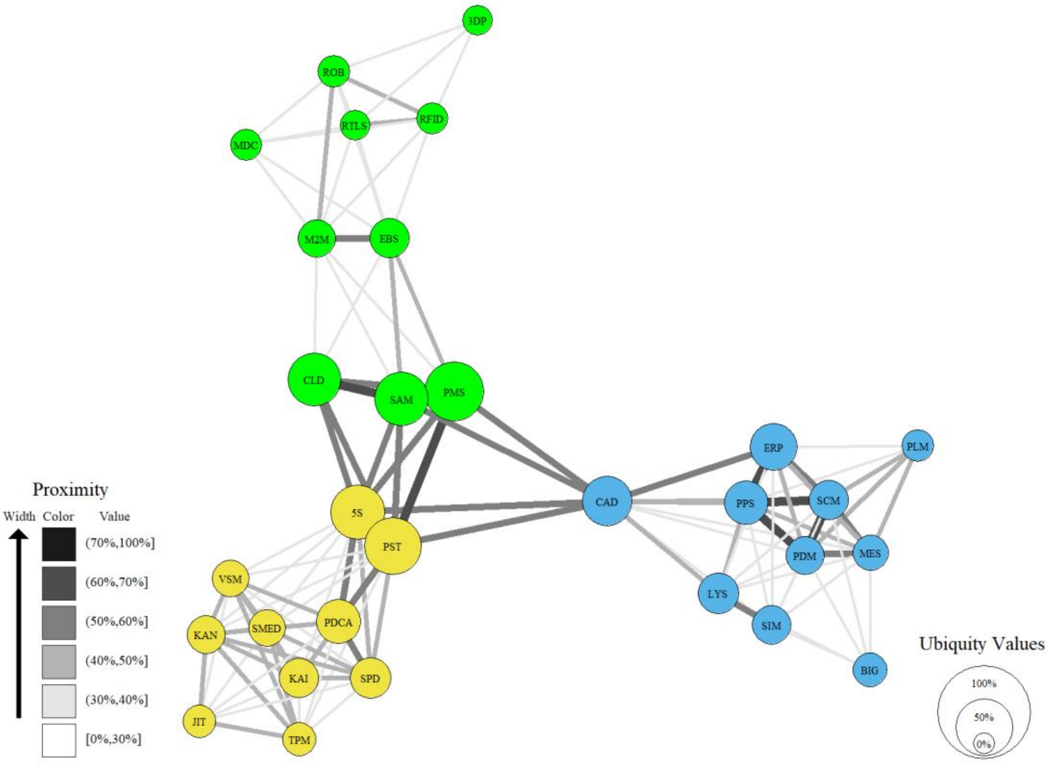

Figure 2. Technology Network Considering All Data.

In addition to the graph representation, the ten highest ubiquity and weighted degree centrality results are presented in Table 2. The degree centrality is widely used as a metric for assessing the importance of nodes and measures the number of edges connected to a specific node, it is weighted because it sums the proximity values for each edge.

Table 2. Metrics of Node Centrality and Ubiquity of the Technology Network.

Technology	Ubiquity	Technology	Weighted degree centrality
PMS	53.1%	PST	5.744
PST	49.8%	5S	5.346
5S	46.6%	CAD	4.953
SAM	45.8%	SCM	4.276
CLD	44.3%	PDM	4.210
CAD	39.9%	PDCA	3.999
ERP	36.2%	PPS	3.942
PDCA	32.0%	SMED	3.900
PPS	31.3%	KAI	3.876
LYS	27.5%	KAN	3.875

Even though the results shown in Table 2 may help to generate insights, questions may naturally arise regarding the technology network's results. It is worth mentioning that certain characteristics of the companies, such as sector, size, region and annual revenue, are not considered in the network of Figure 2. Thus, some technologies may not present the expected result when considering a specific characteristic. For example, a CAD system is probably not as important for a food company as it is for an automotive company. Knowing this, additional networks were generated to verify the influence of the size and industrial segment of companies on the results.

The company size information was given in the questionnaires, enabling a simple sorting of the database to generate company size specific networks. As the literature suggests, large companies usually have more resources to invest on technological applications than small and medium sized companies. This fact also becomes evident when comparing the networks of Figure 3, which only consider the responses of companies characterized as small (left) and large (right).

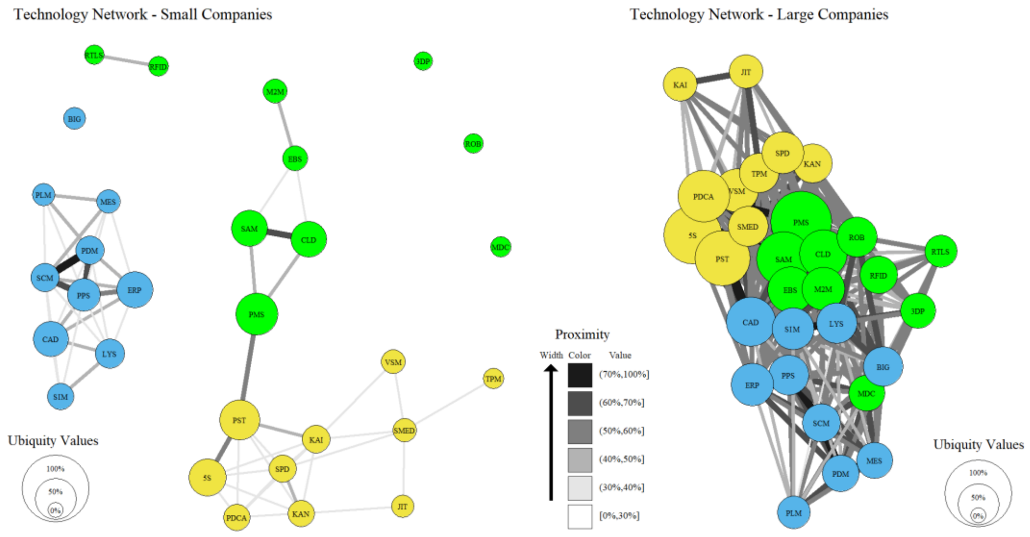

Figure 3. Comparison Between Technology Networks for Small and Large Companies.

Figure 3 shows that small companies have fewer technologies and systems applied than large companies, which have a highly connected and high-density network. Even though this result was expected, it is possible to identify which technologies are being focused by companies of different sizes, as well as to get an idea on how de diffusion process occurs. Besides, it is possible to argue that large companies would prefer not to compare themselves with small and medium sized companies for decision making on technology adoption. This assumption indicates that the technology networks by company size would contribute with more relevant insights than the network of Figure 2 for a group of companies. Nonetheless, it is also proposed to analyze the influence of industrial segments over the results.

As a basis for classification of industrial segment, the main CNAE (National Classification of Economic Activities) registered in the CNPJ of the companies was considered. By applying the network science algorithm for each CNAE division (first two numbers) as factors, it was possible to generate networks for specific industrial segments. In Figure 4, only companies in the automotive vehicle sector are considered, a total of 253 companies that work with the main CNAE of division 29 - Manufacturing of automotive vehicles (IBGE, 2007). This industry segment has the largest number of representatives among the data used.

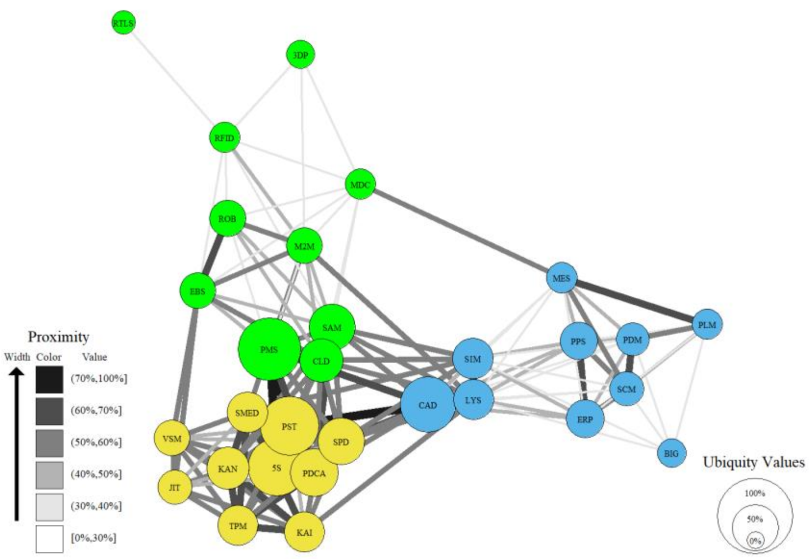

Figure 4. Technology Network for the Automotive Vehicle Segment.

When comparing the automotive vehicles segment with the network of Figure 2, it is possible to notice higher values of ubiquity, as well as more connections between the three areas. Furthermore, it is possible to observe a higher density of vectors. These results indicate that there is greater dissemination of technologies and systems among companies in the respective sector.

The same analysis was performed with data from the food industrial segment, considering 157 companies with the main CNAE in division 10 - Manufacturing of food products (IBGE, 2007). Figure 4 shows the network obtained for the segment. It has a different configuration, with no connections (with a proximity equal or greater than 50%) between the OS and IT areas. In general, the density observed in the disposition of vectors and the ubiquities of this sector are lower when compared to the automotive segment. It can be noticed that the relevance of specific technologies varies a considerable amount, such as CAD, autonomous and collaborative robots (ROB) and layout simulation (LYS).

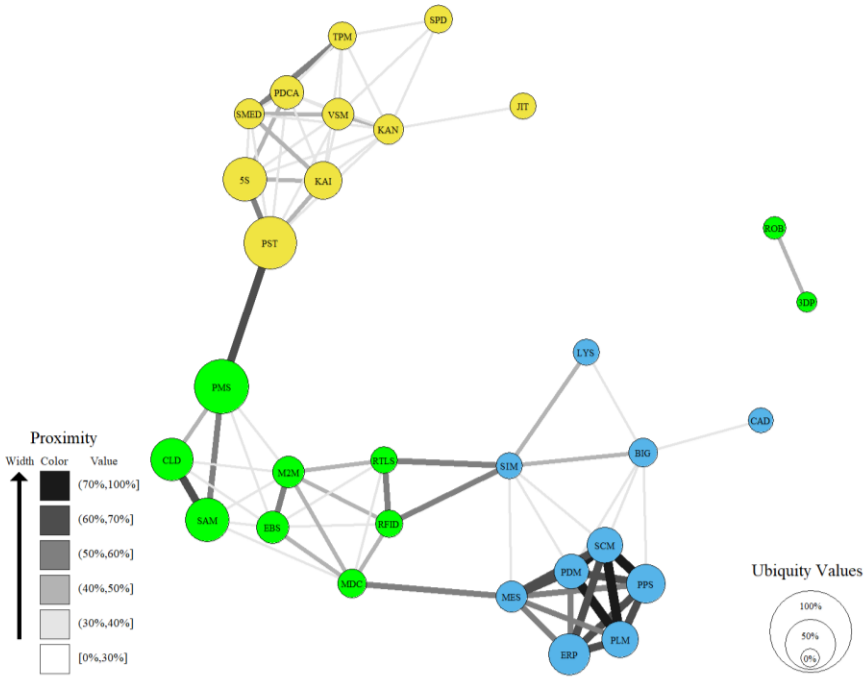

Figure 4. Technology Network for the Food Industrial Segment.

In addition, a network for the chemical segment of CNAE started in 20 - Manufacturing of chemical products (IBGE, 2007) was created. Figure 5 shows the resulting technology network of this segment, which has 42 representatives in the considered database. In general, higher average values of ubiquity and proximity are noticed in comparison to the food segment. Furthermore, it is possible to notice that the operating technologies are centralized in the network, indicating higher degree centrality and connections with other areas.

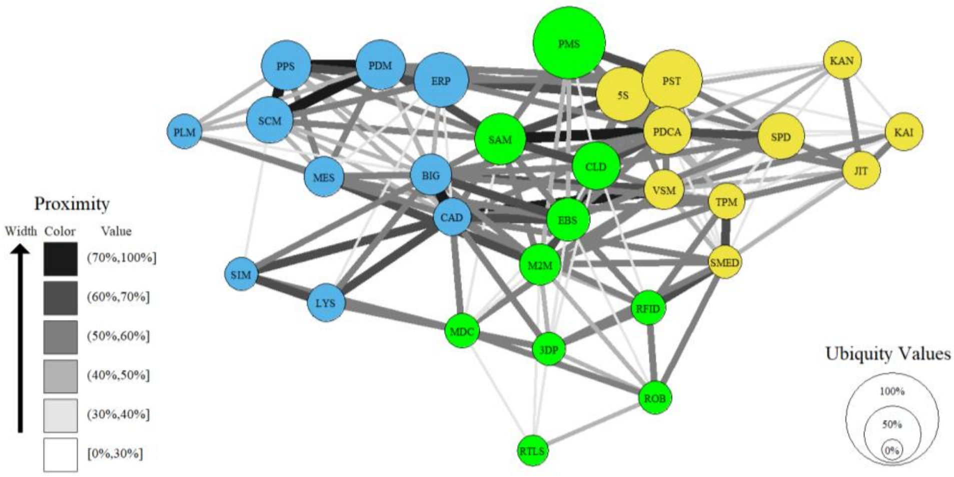

Figure 5. Technology Network for the Chemicals Segment.

The differences observed in the results of the industrial segments reinforced that this factor is critical for the decision-making of technology adoption. For these purposes, it could also be argued that a combination of factors would be most suitable in order to generate a technology network for a specific company. However, the number of data available is greatly reduced when combining factors, which can affect analyses. Therefore, it is advised to study the relevance of the factors for each case and apply them when considered essential.

5. CONCLUSIONS

Considering the technology networks generated, it is suggested that network theory can be used as a decision support tool for the application of manufacturing technologies and systems. The developed networks offer a different way of visualizing technology application data, highlighting the existing patterns in the databases. Also, it is noted that there are technologies that group together into highly connected communities, which suggests that each community uses a similar set of features. That said, the following considerations can be made regarding the development of the networks for decision making on manufacturing technologies:

a) Finding or developing databases that can relate technologies is a critical requirement for the development of the technology networks;

b) Programming the network science algorithm is complex. However, using libraries like igraph facilitate this process;

c) The initial version of the network can expose the data in a confusing way. In such cases, some parameters (edge width, vertex size, lower proximity values etc.) must be studied and adjusted in order to provide better visualization and interpretation;

d) It was found that proximity results for the technologies and systems are affected when considering criteria, such as industrial segment and company size. Therefore, it is suggested that these factors should also be considered in future studies that relate network theory and manufacturing technologies, as well as in subsequent decision-making processes.

Finally, it is possible to argue that there are several opportunities for applying the technology networks. For instance, a continuous monitoring would allow identifying the growth of specific applications. From this it is possible to verify new market opportunities for technology suppliers, as well as to direct public policies. Regarding the contributions to the decision-making process for organizations that want to invest in new technologies, a methodology is to be developed in future work.

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