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Literature review on the "Smart Factory" concept using bibliometric tools

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The objective of this paper is to depict a landscape of the scientific literature on the concept of the 'Smart Factory', which in recent years is gaining more and more attention from academics and practitioners because of significant innovations in the production systems within the manufacturing sector. To achieve this objective, a dynamic methodology called "Systematic Literature Network Analysis (SLNA)" has been applied. This methodology combines the Systematic Literature Review approach with the analysis of bibliographic networks. The adopted methodology allows complementing traditional content-based literature reviews by extracting quantitative information from bibliographic networks to detect emerging topics, and by revealing the dynamic evolution of the scientific production of a discipline. This dynamic analysis allowed highlighting research directions and critical areas for the development of the "Smart Factory". At the same time, it offers insights on the fields on which companies, associations, politicians and technology providers need to focus in order to allow a real transition towards the implementation of large-scale Smart Factory.

Keywords: Systematic Literature Review, Industry 4.0, smart factory, citation network, co-word network.

1. Introduction

Technology advances have always driven the improvements in industrial productivity and the start of industrial revolutions. The first industrial Revolution (starting from 1784: Henry Cort invented a better way of making wrought iron) was characterized by the mechanical weaving loom, water and steam power, mechanical production equipment. The second revolution (starting from 1870 to 1915) was characterized by the mass production, assembly lines using electrical energy. The third revolution (starting around 1970) was characterized by computers and automation, the appearance of the first programmable logic controller (PLC); and the fourth (starting around 2010) is based on cyber-physical systems, i.e. the link of real objects with virtual objects via the information networks, and it is bringing together digital, physical and biological systems. The 'Smart Factory' constitutes a key feature of Industry 4.0, i.e. the fourth industrial revolution (Drath & Horch 2014). Factories become smarter, more efficient, safer and more environmentally sustainable, thanks to the combination and integration of production technologies and devices, Information and Communication systems, data and services in network infrastructures. For example, in a Smart Factory flexibility and re-configurability of production and the interaction with customers (to know their needs) allow customizing goods and services with the same cost-efficiency level as mass production (mass-customization). Other examples include the implementation of the

Internet of Things (IoT) technologies in the Smart factory: e.g. sensors and artificial intelligence drive smart maintenance; mobile and augmented reality devices empower workers to increase the efficiency and agility of their operations with processing of information in real time; and cloud computing systems allow storing data in a network-based sharing environment. Altogether, the implemented technologies allow for the use of resources in an efficient way, making sustainability a key feature of Smart Factories.

Within the context of the fourth industrial revolution, the term “Smart Factory” is being widely used by both industrial practitioners and scholars, but to date a consistent and shared definition of the concept of “Smart Factory” does not exist (Radziwon et al. 2014). Moreover, the current body of knowledge has witnessed a considerable proliferation of journal papers and scientific contributions centred on this concept, showing how it has gained attention and raised to prominence in the academic and practitioners’ communities today. Consequently, the current state of the art on Smart Factory within Industry 4.0 is calling for an investigation aimed at systematizing and rationalizing the produced knowledge on this subject. In doing this, it would be ideal to investigate also the process of creation, transfer and development of knowledge from a dynamic perspective, to unveil its evolution over time rather than just providing a static snapshot of it.

Hence, the goal of this paper is to depict a landscape of the scientific literature on the Smart Factory concept adopting the dynamic literature review method called “Systematic Literature Network Analysis (SLNA)” introduced by Colicchia and Strozzi (2012), which combines systematic literature review and bibliographic network analysis. The adoption of such an approach is deemed an ideal choice for the topic under investigation given its capabilities to embrace the limitless expansion of knowledge. In addition, the successful adoption of such an approach to other contexts, e.g. Kim et al. (2016), Kajikawa et al. (2007), proves its potential value in the identification of trends, evolutionary trajectories and key issues that are influencing the development of knowledge within a field in a more scientific and objective way compared to traditional descriptive reviews. These, in fact, are based on content analyses that fail in encompassing the evolutionary aspect of a field of study and rely on subjective criteria for selecting papers and classifying research contributions on pre-defined coding schemes. SLNA, instead, relies on objective measures and algorithms to perform quantitative literature-based detection of emerging topics.

One of the components of the SLNA method is represented by the analysis of bibliometric networks of the information retrieved, such as citations and keywords networks.

Citation network analysis is a tool that relies on the reference list of journal papers or publications, which point to prior contributions that have influenced their development of the research. The citation is assumed to represent the influence of the cited work on an author’s new work (Zhao and Strotmann 2015). Even though individuals tend to cite papers for a number of subjective reasons, citations are widely used as a proxy of relevance. As Dawson et al. (2014) argued, notwithstanding highly cited papers are not necessarily presenting impactful and high quality research; it is realistic to assume that a large number of received citations reflects a high level of impact and quality. The validity and usefulness of citations to uncover information is demonstrated by the success of Google Web search engine as an example, which implements an algorithm based on citations to detect resources that are both high quality and relevant to users' information needs (Brin and Page 1998).

Nevertheless, taking into account only citations to delineate and represent a field is not a flawless approach. In fact, many papers are discarded in the analysis because any other paper does not cite them, even if their content is important or they seem less relevant in comparison to others because they have been recently published and this prevented them from receiving a large number of citations. To overcome this limitation, it is then important to cross the citation network analysis with other tools such as the Global Citation Score analysis and the keyword analysis.

This paper is structured as follows. In Section 2 materials and methods are presented, while in Section 3 the results of the first phase of the SLNA method are shown, i.e. systematic literature review. In Section 4 the results of the second phase of the SLNA method are described, with particular reference to the performed citation, Global Citation Score and keyword analyses. In Section 5 results are discussed and research directions are identified. Final remarks conclude the paper (Section 6).

2. Material and methods

The data used in this work were collected from the Web of Science (WoS) database, which is, together with Scopus, the most commonly used scholar citation database for field delineation. The WoS, previously known as ISI database, had been the dominant citation database of most citation analysis studies to date.

Scopus is very similar to the WoS database; it has some advantages and disadvantages. The main advantage is that Scopus coverage is nearly 60% larger than the one of WoS (Zhao and Strotmann 2014), but one of the main disadvantages is that the data are not "clean" as the ones of WoS and this implies that some papers are not uniquely identified and can be considered as different nodes in the resulting citation network. This can lead to a wrong analysis of the citation network.

As mentioned, the procedure chosen to extract and analyse the papers is the Systematic Literature Network Analysis (SLNA). SLNA (see Figure 1) consists of two phases.

In the first phase a Systematic Literature Review (SLR) is performed, and the definition of the scope of the study is identified by means of three steps:

1. Scope of the analysis. To formulate the research question and to frame a correct literature review Denyer and Tranfield (2009) proposed the answer to the questions related to Context, Intervention, Mechanism and Outcome (CIMO).

2. Locating studies “keywords, time, type of documents, language”
3. Study selection and evaluation.

The output of this phase will be a set of selected papers.

The second phase of SLNA methodology consists in the bibliographic network analysis and visualization. In particular, in this work, the citation network and the keywords network will be considered, in accordance with the steps of the methodology depicted in Figure 1.

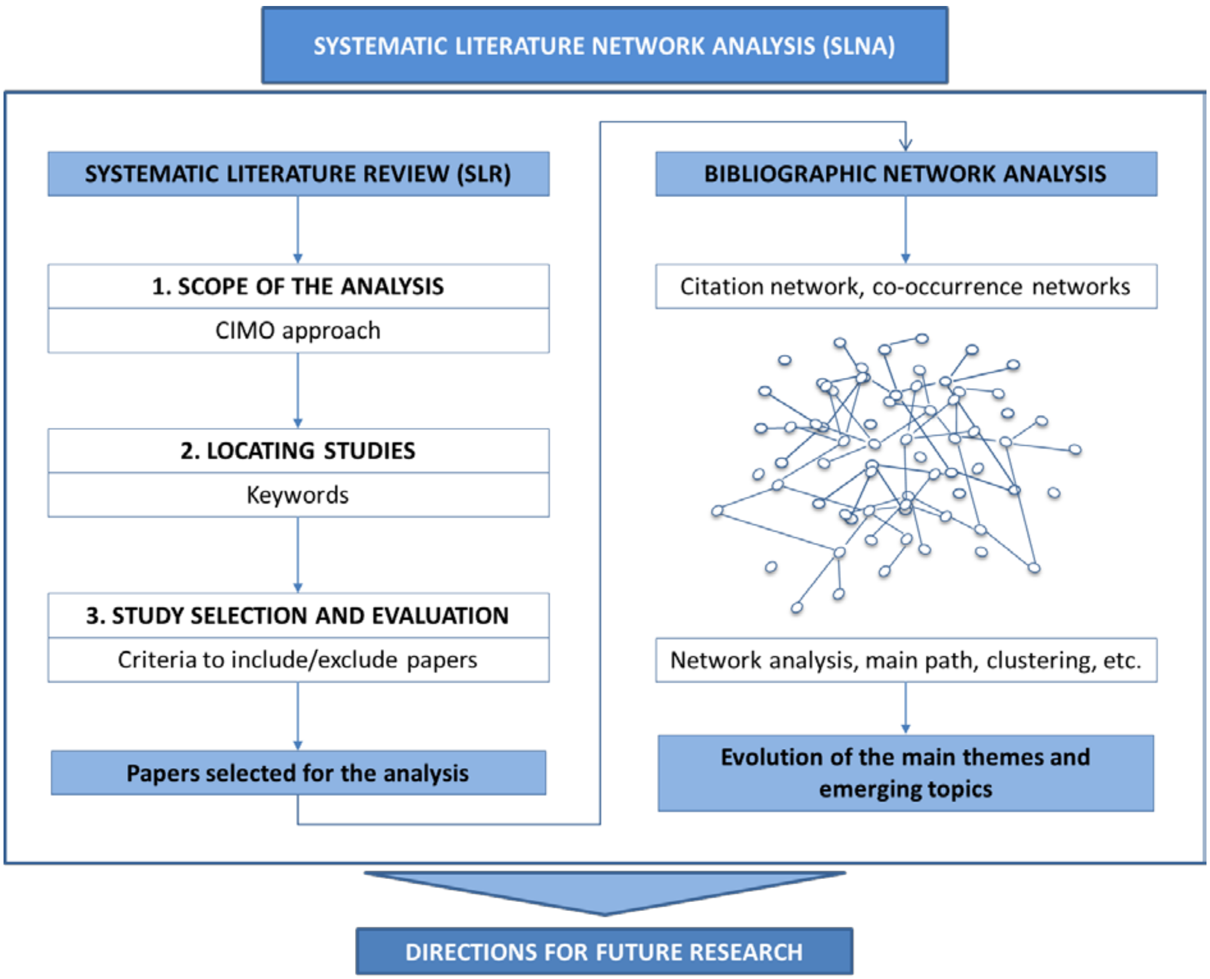

Figure 1. Systematic Literature Network Analysis (SLNA).

To build the networks different software packages were adopted. Sci2 Tool (http://cns.iu.indiana.edu) is a modular toolset specifically designed for the study of science and it supports the temporal, geospatial, topical and network analysis and visualization of datasets. In this work, Sci2 was used to build citation networks and generate the input file for Pajek. Pajek (De Nooy et al. 2005) is software for Social Network Analysis and, in this work, it was used to represent and to study the citation networks. VoS viewer (http://www.vosviewer.com/) is another software tool able to analyse bibliometric networks and, in this work, it was used to study keywords network applying the VoS clustering methodology (Van Eck and Waltman 2009).

3. First phase of SLNA methodology: SLR

3.1. Scope of the analysis

In this paper the concept of the "Smart Factory" was studied. A Smart Factory is a production plant where the pillars of Industrie 4.0 are implemented i.e. additive manufacturing, augmented reality, Internet of Things, Big data analytics, autonomous robot, simulation, cyber-security, vertical and horizontal integration and cloud (The Boston Consulting Group 2016). The Smart Factory relies on Cloud computing and operates in a network in which companies, suppliers and customers are closely linked and the human factor is fundamental. As mentioned, since the German government announced the launch of "Industrie 4.0" as one of the key initiatives of its high-tech strategy in 2011 (Kagermann, et al. 2013) many academicals and not academicals publications appeared on this topic.

3.2. Locating studies

The identification of the keywords was performed as follows: a set of different synonyms of "*smart factory*" in the academic literature was identified and then confirmed by a team of academics and production managers. Different synonyms of the term "smart" exist in the literature, such as "intelligent", "real-time" or "ubiquitous". The concept of "ubiquitous" was introduced by Weiser in 1991 to indicate the pervasive use of computing in real life, and later used by many authors to indicate the pervasive use of sensors and computing in a factory that becomes a "ubiquitous factory". The capability of different "parts" of the factory to interact among them, and directly with customers and suppliers thanks to the implementation of ubiquitous computing transforms the factory in a Factory of Things - in analogy with the Internet of Things. Finally, "Manufacturing" is often used in the literature instead of "Factory".

The set of identified keywords follows: "smart factory" OR "intelligent factory" OR "ubiquitous factory" OR "real-time factory" OR "smart factories" OR "smarter factories" OR "intelligent factories" OR "ubiquitous factories" OR "real-time factories" OR "smart manufacturing" OR "smarter manufacturing" OR "intelligent manufacturing" OR "ubiquitous manufacturing" OR "real-time manufacturing" OR "factory-of-things".

This step of the analysis is very critical and results may change if different keywords are used. Given the novelty of the investigated subject, the chosen set of keywords relates to the concept of smart factory and its synonyms. As abovementioned, one of the tasks of the panel of experts was to discuss the possible different synonyms of the investigated concept in order to include those terms most commonly used. Since this process might imply a certain degree of subjectivity (notwithstanding the reduction of personal bias thanks to the interaction of different individuals from the academic and industrial communities), it is important to apply different tools to extract information from a set of papers and discuss results in the light of contextual factors (e.g. governmental actions, published policies) to offset this problem. Additionally, specific terms related to the features of the smart factory were not included in the set of chosen keywords at this stage, since this would have restricted the number of retrieved papers, given the specificity of these terms that narrow the search. This choice was discussed in the panel of experts (see above) and it was made in compliance with the objective of this work, i.e. to depict a landscape of the scientific literature on the smart factory concept. The chosen set of keywords allows specific concepts and related issues and trends to emerge through the application of the adopted methodology and its bibliographic analysis tools.

3.3. Study selection and evaluation

The identified keywords were used as search terms in WoS in late May 2016 in the "Title" field in order to select the papers having the Smart Factory as the main goal of their analysis. Only papers published in English and only articles or proceedings published between 2007 and 2016 were considered. This led to obtain 462 works as a search outcome. This time window was selected in order to encompass the beginning of the governments' efforts to accelerate the advent of the fourth industrial revolution (of which the Smart Factory represents an important feature) and to detect changes in the directions research has taken over time.

4. Second phase of SLNA methodology: bibliographic network analysis

The Systematic Literature Review allowed identifying the most relevant papers and hence performing a first selection of the contributions to be included in the analysis. The 462 papers resulting from the SLR process were included in the citation network analysis in order to investigate the process of knowledge creation, transfer and development in the field of the Smart Factory.

4.1. Citation Network Analysis (CNA)

A citation network is a network where the nodes are papers and the links are citations. The arrows go from cited to citing papers representing the flow of knowledge. In Figure 2 the citation network related to this work is showed and, as it is possible to see, it is composed of many isolated nodes and some connected components. A connected component is defined as a set of nodes connected by links, i.e. citations.

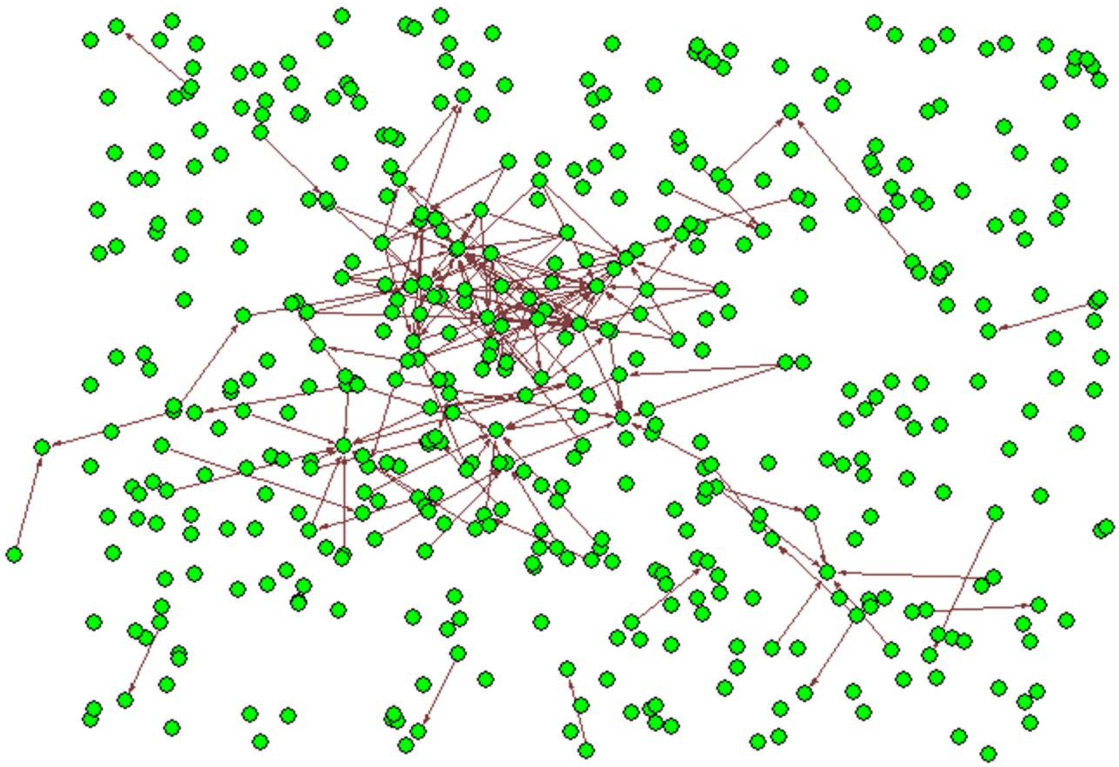

Figure 2. Citation network of 462 papers.

Depending on the citation links, it is possible to have connected components with only a few nodes and others with a higher number of nodes. Since CNA is a method based on citations, the “isolated” nodes are excluded from the analysis since not connected by definition. In fact, the citation analysis can be applied only on the connected components. Additionally, it gives the best results when connected components are composed of a large number of nodes, since the amount of information that can be extracted is much bigger than the one emerging from small components with only a very limited number of connected nodes (Strozzi et al. 2014). Based on these considerations, in this work, the first three biggest connected components were analysed.

4.1.1. The biggest Connected Component

Figure 3 depicts the biggest connected component, which includes 43 nodes.

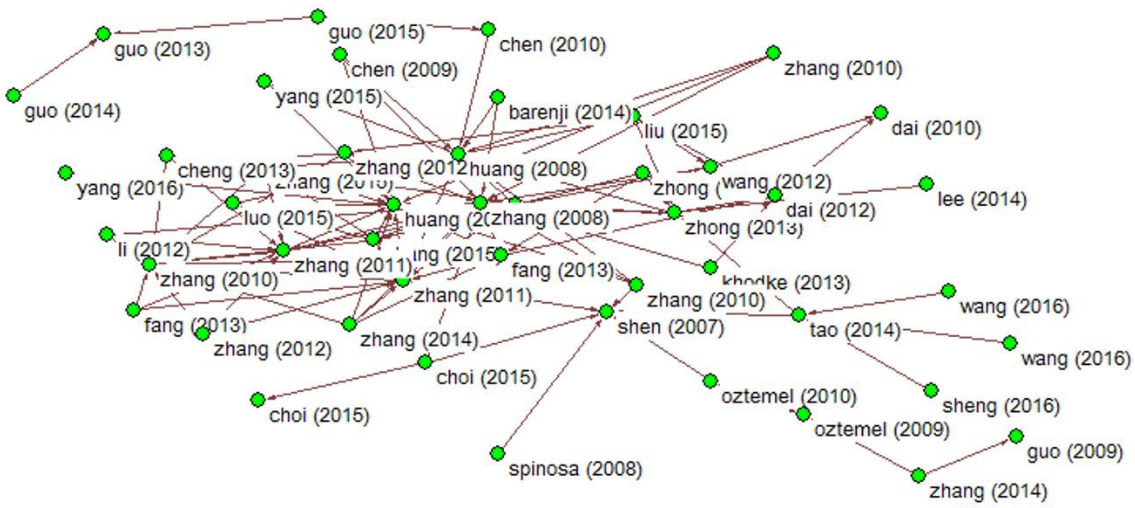

Figure 3. First biggest connected component of the citation network.

Given the size of this component, in order to detect the existence of a main trend in the evolution of the paper contents it is useful to extract the so-called Main Path component (Lucio-Arias and Leydesdorff 2008). Main Path helps to obtain a dynamic perspective of a set of connected papers identifying the most relevant ones published at different time that constitute the backbone of the research tradition (De Nooy et al. 2005; Lucio-Arias and Leydesdorff 2008). In fact, the Main Path highlights the articles that build on prior articles but continue to act as hubs in reference to later works. Main Path is a useful instrument to distill connected components with many nodes. The two steps to perform Main Path Analysis are the following:

1. Quantifying the citation traversal weights, i.e. the extent to which a particular citation is necessary to link articles. Different methods exist to calculate traversal weights; in this work, *Search Path Count* was applied. It considers all paths from each source (i.e. an article that is not citing any others) to each sink (i.e. an article that is not cited by others), the weight of the citation is given by the ratio between the number of paths including the citation and the total number of paths between the sources and sinks;
2. Extracting component Main Path. Using the traversal weights of articles and citations it is possible to extract the Main Path that will identify the main streams of the considered literature, that is, in our case, the set of 43 papers.

A cut-off value between 0 and 1 is used to remove all arcs in the original citation network with a lower value of transversal weight. In this work the cut-off default value of Pajek software, i.e. 0.5. was used.

In Figure 4 the Main Path of the biggest component is presented (see appendix). The papers range from 2007 to 2016 and their main subject is the Radio-Frequency Identification (RFID) technology together with the agent-based intelligent decision support system architecture to handle the monitoring and the scheduling of production. In fact, in the smart factory, the objects become smart and they can take autonomous decisions: in this case, they are called "agents".

Figure 4. The Main Path of the biggest connected component of the citation network.

RFID and sensors in general are important components of a smart factory where the objects with limited intelligence allow controlling the global manufacturing process. The main path component seems to be dominated by few authors: Zhang and Huang. Another interesting result is that the National Science Foundation of China financially supported many papers of the Main Path.

The oldest paper of this component, Shen et al. (2007) - i.e. node 8, proposed an agent-based service-oriented integration architecture to leverage manufacturing scheduling services on a network of virtual enterprises. The scheduling process of an order is orchestrated on the internet through the negotiation among agent-based web services. Later, Zhang (2010), Zhang et al. (2011a), and Zhang et al. (2011b) - i.e. nodes 3, 10, and 9, proposed to use agent-based workflow management as a mechanism to facilitate interactions among smart reconfigurable manufacturing resources. In particular, node 10 seems to act as a "sink" for the others, since many arrows coming from other nodes point to it. This topology is typical of a literature review or a summary on the subject, but since the same author names appear several times, this can be seen as an indication of self-citation phenomena. This confirms, in any case, that these few authors are among the most active in this field. Fang et al. (2013) - node 4 - proposed an event-driven (Critical Event Model) shop floor work-in-process management platform for creating ubiquitous manufacturing. Luo et al. (2015), node 5, proposed an implementation of RFID technologies for real-time planning and scheduling and developed a multi-period hierarchical scheduling mechanism.

4.1.2. Second biggest Connected Component

In the second biggest connected component (Figure 5, and appendix), a central node emerges: Davis et al. (2012), node 2. In this paper the authors defined smart manufacturing as a “dramatically and pervasive application of networked information-based technologies throughout the manufacturing and supply chain enterprise” and they analysed the US landscape. They said that in 2012 in the US there was still a debate if the governments had to act to enhance the process of smart manufacturing (tax policies, new workforce education, etc.) or “leave it to industry and to the market”. Only in 2014 the US government supported research and development activities in the area of smart manufacturing (Council Advisors on Science and Technology 2014). On the contrary, other countries have enacted government level plans to invest and accelerate changes in manufacturing (European Commission 2009; EPSRC 2011; Fraunhofer 2011). Davis et al. (2012) analysed the reason why, even though the smart manufacturing seems a promising idea, many companies were still hesitating to adopt it. These reasons may be different: the basic architecture of the traditional Distributed Control Systems precludes the use of “Smart Manufacturing” technologies; investments in these technologies may be justified and their cost could be affordable for large companies, but remain essentially prohibitive for small and medium manufacturers. In addition, a modern industrial infrastructure and incentives to avoid an uncoordinated application of these technologies, resulting in a piecemeal implementation, are necessary to allow a real transition to the Smart Factory.

Figure 5. Second biggest connected component of the citation network.

The paper by Davis et al. (2012) was published in “Computer and Chemical Engineering” and it is interesting to note that some other papers published in academic journals of the same discipline cited it: AICHE (Lao et al. 2014, node 1) and Industrial and Engineering Chemistry Research (Kumar et al. 2015, node 7). These papers deal with issues related to the Smart Factory in the chemical industry, such as sustainability and the ability to adapt to rapidly changing requirements of production control. Others papers are more related to managerial aspects such as the capability to rapidly adapt to demand fluctuations and the related problem of product quality (Kim et al. 2015, Jung et al. 2015).

4.1.3. Third biggest connected component

In Figure 6 the third biggest connected component is shown (see appendix). The central node of this component is the paper by Zuehlke (2010), node 4. It describes the "SmartFactoryKL" initiative funded by a set of industrial and academic partners in Germany to create and operate a demonstration and research test bed for "the future factory" technologies. This paper has a "high out-degree", i.e. many other papers cited it. A possible interpretation of this result is that this paper can be regarded as a seminal work or a milestone in the development of the Smart Factory concept.

Figure 6. Third biggest connected component of the citation network.

The other papers of this component can be grouped as follows. Zamifirescu et al. (2013), Kannengiesser and Muller (2013) and Kannengiesser et al. (2015), i.e. nodes 3, 7, 10, integrated human agents and artificial ones across all level of industrial control. Kassner et al. (2015), i.e. node 9, Fisher et al. (2013), i.e. node 1, and Rashid et al. (2012), i.e. node 2, considered different aspects of the manufacturing operations that have to be taken into account to have a real Smart Factory (i.e. data analytic, novel query language and Enterprise Resource Planning, ERP, with a scenario planning). Radziwon et al. (2014), i.e. node 5, collected different definitions of the Smart Factory concept. It is possible to observe that the papers just mentioned were written by authors affiliated to European universities or institutions (Zamifrescu et al. (2013) from DFKI – German Research Center for Artificial Intelligence, Innovative Factory Systems; Kassner et al. (2015) from University of Stuttgart; Radziwon et al. (2014) from Mads Clausen Institute, University of Southern Denmark, and the Institute of Technology and Innovation, University of Southern Denmark; Kannengiesser et al. (2013) from Metasonic AG Pfaffenhofen, Germany). Other papers preferred to adopt the terminology of "ubiquitous manufacturing", more widely used in

US, instead of Smart Factory and proposed different methods to implement it in the factory (Mejia-Gutierrez et al. (2015), i.e. node 6, Suh et al. (2008) i.e. node 8, Yoon et al. (2012) i.e. node 11).

4.1.4. General Comments on the three biggest connected components

An overview of the three biggest connected components allows observing that the papers of the Main Path of the first component (funded by the National Science Foundation of China) are focused on the RFID technology and multi-agent interaction as main themes. The second component is developing around the paper of Davis et al. (2012), i.e. node 2, describing the Smart Manufacturing landscape from the political and economic point of view, along with the efforts to accelerate the process of adoption of the Smart Factory in the US. In the third component a European view of the process is given by Zuehlke (2010) together with suggestions on how to implement the Smart Factory concept from the managerial point of view.

It seems that citation network analysis highlights research interests and activities on the Smart Factory concept in China, USA, and Europe, and it seems that a certain disconnection in terms of research focus among these three different geographical areas exist. This could be explained also by the use of different terms for referring to the concept of "Smart Factory" in the different geographical context, which can affect the citations among groups. Taking into account the first connected component (including the research activities mainly conducted in China) the term "real-time manufacturing" appears six out eleven times in the title of papers and "ubiquitous manufacturing" three out eleven times. This might imply a more specific interest in the enabling technologies such as wireless sensors. A recent survey by the consultancy company Staufen (2015) shows that China is leading the development of the enabling technologies of the Smart Factory, with more than 2500 patent registrations, compared to 1065 registrations in the USA and 441 in Germany. In the second connected component including the contributions from the USA, in nine out of ten times authors used the term "Smart Manufacturing" in their titles. This can be related to the emphasis that the American federal government is placing on the re-development of the manufacturing capabilities of the country, with many initiatives related to advancing the concept of Industry 4.0. Finally, in the third connected component, including the works carried out by European researchers, in nine times out of twelve, the term "Smart Factory" appears in the title. This term has become of common use across Europe after the contribution by Zuehlke (2010), where he first introduced this term, which was adopted also in governmental initiatives.

Besides the difference in the main focus and terminology used in the papers, two elements still emerge as common factors driving research, regardless the concerned geographical area: the emphasis on the key role of governments in the development of the Smart Factory initiatives and the importance of the financial support (coming from public and private funding sources) for making the Smart Factory possible. The analysed papers show that governments started to enhance the process of smart manufacturing to accelerate the development of the fourth industrial revolution and planned some kind of agenda.

The second interesting finding of our analyses is that the Smart Factory is a pervasive concept and it extends in its nature beyond the boundaries of the focal manufacturing unit. Hence, the authors of the reviewed papers stress the necessity to implement the concept of the Smart Factory broadening its perspective at the level of the entire supply chain, focusing also on the connections existing among the various tiers of production/supply chain networks. This seems to be a condition necessary to achieve a holistic and systemic approach to the development of the Smart Factory. Likewise, such an approach would avoid isolated implementations of single initiatives that could result in a "piecemeal" development and diffusion of the Smart Factory.

As mentioned, in the citation network some papers out of the retrieved set of scientific works were not included in this analysis because there are no citations linking them and they could not be included in any of the three biggest connected components. This especially applies to new fields of study, such as the Smart Factory, which usually present a rather disconnected citation network. To compensate this shortcoming, it is possible to perform additional analyses, i.e. Global Citation Score (GCS) analysis and the author keywords analysis, as showed in the following sections.

4.2. Global Citation Score analysis

GCS analysis can be used to detect seminal or recent breakthrough studies. GCS shows the total number of citations to a paper in WoS database regardless their inclusion in a connected component of a citation network. Papers with high GCS are recognized as seminal or influential papers in the body of knowledge (Knoke and Yang, 2008). In other words, GCS is able to identify the papers that represent the basis of a field and used by authors for the development of their contributions, including citations from articles of the whole Web of Science database, even if these citing papers were not selected through the keyword search. Table 1 reports the 10 most cited papers ranked according to their GCS, along with their Local Citation Score (LCS). LCS shows the number of citations that a paper received within the citation network. GCS and LCS were retrieved from WoS after the complete indexing for year 2016 of the WoS database, in order to include all citations received by papers in 2016. By comparing GCS to LCS, it is possible to identify seminal works that received a small number of citations within the citation network but that received a considerable amount of citations in the whole WoS database. As Table 1 shows, it is interesting to notice that in the top 10 cited papers, three studies do not belong to any of the three analysed biggest connected components. Table 1 confirms that some of the papers belonging to the three biggest connected components are indeed seminal works in the field, and not only within the citation network. Also, the three additional papers confirm the main subjects that are receiving consideration by the scientific community over time (e.g. enabling technologies).

Table 1 - GCS and LCS of the 10 most cited papers

Rank	Title	Author	Journal	Publication year	GCS	LCS	Part of the biggest connected components
1	An agent-based service-oriented integration architecture for collaborative intelligent manufacturing	Shen, Welming; Hao, Qi; Wang, Shuying; Lia, Yinsheng; Ghenniwa, Hamada	ROBOTICS AND COMPUTER-INTEGRATED MANUFACTURING	2007	81	6	x
2	SmartFactory-Towards a factory-of-things	Zuehlke, Detlef	ANNUAL REVIEWS IN CONTROL	2010	73	10	x
3	RFID-enabled real-time manufacturing execution system for mass-customization production	Zhong, Ray Y.; Dai, Q. Y.; Qu, T.; Hu, G. J.; Huang, George Q.	ROBOTICS AND COMPUTER-INTEGRATED MANUFACTURING	2013	71	5	x
4	RFID-based wireless manufacturing for real-time management of job shop WIP inventories	Huang, George Q.; Zhang, Y. F.; Jiang, P. Y.	INTERNATIONAL JOURNAL OF ADVANCED MANUFACTURING TECHNOLOGY	2008	65	14	x
5	IoT-Based Intelligent Perception and Access of Manufacturing Resource Toward Cloud Manufacturing	Tao, Fei; Zuo, Ying; Xu, Li Da; Zhang, Lin	IEEE TRANSACTIONS ON INDUSTRIAL INFORMATICS	2014	63	3	
6	Modular wireless real-time sensor/actuator network for factory automation applications	Koerber, Hans-Joerg; Wattar, Housam; Scholl, Gerd	IEEE TRANSACTIONS ON INDUSTRIAL INFORMATICS	2007	56	1	
7	Smart manufacturing, manufacturing intelligence and demand-dynamic performance	Davis, Jim; Edgar, Thomas; Porter, James; Bernaden, John; Sarli, Michael	COMPUTERS & CHEMICAL ENGINEERING	2012	53	7	x
8	RFID-enabled real-time Wireless Manufacturing for adaptive assembly planning and control	Huang, George Q.; Zhang, Y. F.; Chen, X.; Newman, Stephen T.	JOURNAL OF INTELLIGENT MANUFACTURING	2008	52	15	x
9	Agent-based workflow management for RFID-enabled real-time reconfigurable manufacturing	Zhang, YingFeng; Huang, George Q.; Qu, Ting; Ho, Oscar	INTERNATIONAL JOURNAL OF COMPUTER INTEGRATED MANUFACTURING	2010	38	1	x
10	A novel approach for multi-agent-based Intelligent Manufacturing System	Guo, Qinglin; Zhang, Ming	INFORMATION SCIENCES	2009	35	1	

Key: GCS = global citation score shows the total number of citations to a paper in the Web of Science; LCS = local citation score shows the count of citations to a paper within the collection.

In order to identify breakthrough recent papers, which represent potentially impactful and promising scientific contributions on the subject, we ranked papers according to the number of citations received in the entire WoS database in the last year (i.e. 2016), divided by the number of years since publication. This allows identifying those papers that have (potentially) low GCS, but that are gaining considerable attention from the scientific community in recent times. In fact, through this process, we "weigh" the citations received in 2016 on the "lifespan" of papers. Table 2 reports the resulting ranking, including also the GCS of papers and received citations in the entire time window we adopted for the search (2007-2016). This analysis allows identifying seven papers that were not included in the previous GCS ranking (see Table 1) and five papers that were not part of any of the analysed biggest connected components. These five additional papers complement the contribution of the already analysed papers belonging to the connected components. All together the papers included in Table 2 seem to suggest that the recent breakthrough literature is moving towards cutting edge topics such as real-time data and information management, cloud computing and big data analytics that empower enabling technologies and allow the implementation of the Smart Factory.

Table 2 - Ranking of the top 10 cited papers in 2016 (citations divided by the number of years since publication)

							Citations received in										
Rank	**Title**	**Author**	**Journal**	**Publication year**	**GCS**	**Part of the biggest connected components**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**Citations 2016/ years since publication**
1	IoT-Based Intelligent Perception and Access of Manufacturing Resource Toward Cloud Manufacturing	Tao, Fei; Zuo, Ying; Xu, Li Da; Zhang, Lin	IEEE TRANSACTIONS ON INDUSTRIAL INFORMATICS	2014	63		0	0	0	0	0	0	0	4	7	51	17
2	RFID-enabled real-time manufacturing execution system for mass-customization production	Zhong, Ray Y.; Dai, Q. Y.; Qu, T.; Hu, G. J.; Huang, George Q.	ROBOTICS AND COMPUTER-INTEGRATED MANUFACTURING	2013	71	x	0	0	0	0	0	0	5	17	23	24	6
3	A dynamic model and an algorithm for short-term supply chain scheduling in the smart factory industry 4.0	Ivanov, Dmitry; Dolgui, Alexandre; Sokolov, Boris; Werner, Frank; Ivanova, Marina	INTERNATIONAL JOURNAL OF PRODUCTION RESEARCH	2016	7	x	0	0	0	0	0	0	0	0	0	6	6
4	Real-time information capturing and integration framework of the internet of manufacturing things	Zhang, Yingfeng; Zhang, Geng; Wang, Junqiang; Sun, Shudong; Si, Shubin; Yang, Teng	INTERNATIONAL JOURNAL OF COMPUTER INTEGRATED MANUFACTURING	2015	20	x	0	0	0	0	0	0	0	0	8	11	5.5
5	Towards smart factory for industry 4.0: a self-organized multi-agent system with big data based feedback and	Wang, Shiyong; Wan, Jiafu; Zhang, Daqiang; Li, Di; Zhang, Chunhua	COMPUTER NETWORKS	2016	6		0	0	0	0	0	0	0	0	0	5	5
6	Implementing Smart Factory of Industrie 4.0: An Outlook	Wang, Shiyong; Wan, Jiafu; Li, Di; Zhang, Chunhua	INTERNATIONAL JOURNAL OF DISTRIBUTED SENSOR NETWORKS	2016	6		0	0	0	0	0	0	0	0	0	5	5
7	IoT-based real-time production logistics synchronization system under smart cloud manufacturing	Qu, T.; Lei, S. P.; Wang, Z. Z.; Nie, D. X.; Chen, X.; Huang, George Q.	INTERNATIONAL JOURNAL OF ADVANCED MANUFACTURING TECHNOLOGY	2016	53		0	0	0	0	0	0	0	0	0	5	5
8	Smart manufacturing, manufacturing intelligence and demand-dynamic performance	Davis, Jim; Edgar, Thomas; Porter, James; Bernaden, John; Sarli, Michael	COMPUTERS & CHEMICAL ENGINEERING	2012	5	x	0	0	0	0	0	0	0	8	19	23	4.6
9	An optimization method for shopfloor material handling based on real-time and multi-source manufacturing data	Zhang, Yingfeng; Zhang, Geng; Du, Wei; Wang, Junqiang; Ali, Ebad; Sun, Shudong	INTERNATIONAL JOURNAL OF PRODUCTION ECONOMICS	2015	9		0	0	0	0	0	0	0	0	1	7	3.5
10	The Smart Factory: Exploring Adaptive and Flexible Manufacturing Solutions	Radziwon, Agnieszka; Bilberg, Arne; Bogers, Marcel; Madsen, Erik Skov	24TH DAAAM INTERNATIONAL SYMPOSIUM ON INTELLIGENT MANUFACTURING AND AUTOMATION	2014	14	x	0	0	0	0	0	0	0	0	3	10	3.3

Key: GCS = global citation score shows the total number of citations to a paper in the Web of Science.

4.3. Author Keywords analysis

Author keywords analysis can be helpful to detect research trends embracing the information available in all papers. In the following paragraphs the author keywords networks (Ding et al. 2001) of the whole set of works retrieved have been studied.

4.3.1. Co-occurrence analysis of Authors' keywords

To analyze the authors' keywords a co-occurrence (or co-word) network (Callon 1991) has been built. In this work the co-occurrence networks nodes are the authors' keywords of the 462 papers and the link weights represent how many times the words appear together in the same papers. Co-occurrence analysis is based on the assumption that the authors' keywords of a paper constitute an adequate description of the content or of the relationship that the paper establishes among investigated problems. The presence of many co-occurrences around the same word or pair of words may correspond to a research theme and it reveals patterns and trends in a specific discipline (Ding et al. 2001).

To perform the co-occurrence analysis, first the authors' keywords of the 462 papers selected in WoS were extracted; second, they were "normalized" i.e. the text was separated into token words, normalized in lowercase, the "s" at the end of words was deleted, the dots from acronyms removed, the stop words deleted. As a result, a “co-word” network was built, taking into account all keywords that appear together for at least five times (i.e. the software’s default value)

In this work the co-occurrence keyword network was analyzed using VOSviewer software (Van Eck and Waltman, 2010) which implements the VOS (*Visualization Of Similarities)* clustering technique. VOSviewer determines the locations of items in a map by minimizing a function depending on a similarity measure (*ASij*) between items defined as:

$$AS_{ij} = \frac{c_{ij}}{c_i c_j} \tag{1}$$

where *cij* is the measure of the co-occurrence of keywords *i* and *j* in the same document and *ci* and *cj* are the expected number of co-occurrences of *i* and *j* under the assumption that the co-occurrences of *i* and *j* are statistically independent.

In Figure 7 and Table 3 the results obtained analysing the author keywords of the 462 papers from 2007 to 2016 are shown.

Research trajectories using author keywords

In this section the keywords clusters/communities (Figure 7 and Table 3) have been analysed and the research trajectories are identified together with the description of some works on the subjects.

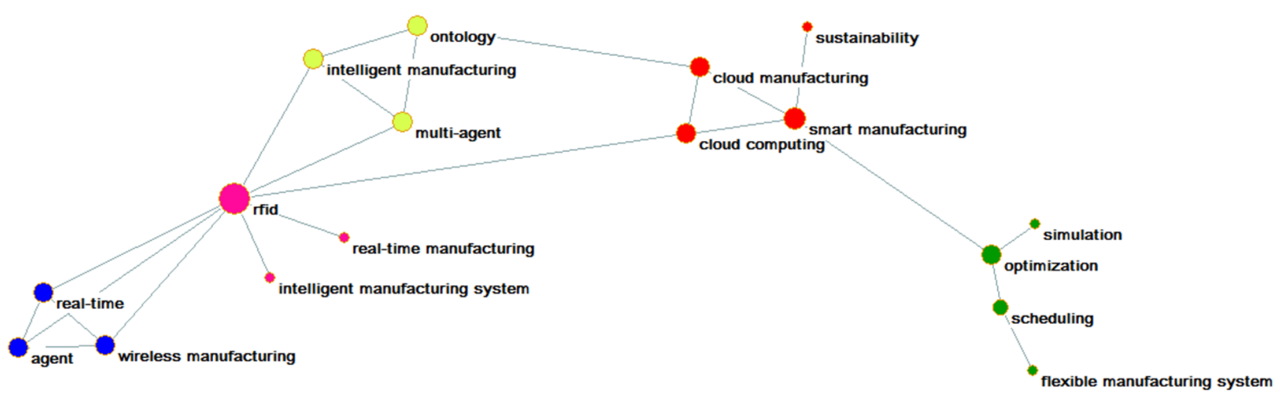

Figure 7. Co-occurrence network of author keywords

Table 3. Clusters identified using VOS Clustering algorithm.

Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5
- Real time - Wireless manufacturing - Agent	- RFID - Intelligent manufacturing system - Real time manufacturing	- Intelligent manufacturing - Ontology - Multi agent	- Smart manufacturing - Cloud computing - Cloud manufacturing - Sustainability	- Optimization - Flexible manufacturing system - Scheduling - Simulation

Cluster 1: real-time, wireless manufacturing and agent

Wireless manufacturing has emerged as a next-generation advanced manufacturing technology. It relies on wireless devices such as Auto ID (Automatic IDentification), RFID (Radio Frequency IDentification) or sensors, and wireless information/communication networks such as Wi-Fi for synchronization and collection or manufacturing field data. Huang et al (2009) discussed the developments of RFID-based wireless manufacturing solutions.

Advances in wireless technologies have created opportunities for developing reconfigurable wireless manufacturing systems with real-time visibility, traceability and interoperability in shop-floor execution, control and planning. Zhang et al. (2010) proposed to use agent-based workflow management as a mechanism to facilitate interactions among RFID-enabled reconfigurable manufacturing resources.

Recent developments in wireless sensors, communication and information network technologies have given birth to the new era of the Internet of Things (IoT). Zhang et al.al (2012) presented the Internet of manufacturing Things (IoMT) to achieve the real-time data capturing from shop-floor front lines along with full connectivity and interoperability among enterprise layers. Key technologies such as sensing and capturing of manufacturing data, configuration of sensor networks, data processing and applications services are designed and analysed under this IoMT framework. The proposed IoMT framework and its key technologies will facilitate the real-time information optimum control and the efficiency of operations during the manufacturing execution process and its management.

Cluster 2: RFID, intelligent manufacturing system and real-time manufacturing

Mass-Customization Production (MCP) companies must fight the shop-floor uncertainty and complexity caused by a wide variety of product components. The scheduling based on paper identification and manual data collection can be inefficient given the current requirements. For example, Zhong et al. (2013) presented a real-time manufacturing execution system based on RFID technology. RFID devices are distributed on the shop floor to track and trace manufacturing objects and collect production data in real-time. Disturbances are identified and controlled within the developed real-time communication and control system. Cluster 2 can be considered a sub-cluster of cluster 1 in the sense that RFID is one (of the first) wireless technologies adopted in the manufacturing environment.

Cluster 3: intelligent manufacturing, ontology and multi-agent

The smart manufacturing systems present analogies with the organization of some living systems such as schools of fish, ant colonies and bee's foraging behaviours. The resources of a smart manufacturing system can be considered as autonomous organisms and, likewise the living system, the manufacturing system has the characteristics of self-adaptation, self-healing and self-diagnosis. The algorithms inspired to living systems can be applied to smart manufacturing. Park et al. (2015) considered a cloud based smart manufacturing system for machining transmission cases and they used an advanced information and communication technology such as cognitive agent, swarm intelligence, and cloud computing to integrate, organize and allocate the machining resources.

In computer science and information science, *ontology* is the "description of the concepts and relationships that can formally exist for an agent or a community of agents" (Grouber 1993). Consequently, its meaning is different compared to the one commonly given to this term in the philosophical disciplines, where it refers to the study of the nature of being. Tai et al. (2013) developed an intelligent algorithm for matching supply and demand based on ontology semantic similarities considering demand attributes. Liu et al (2014) proposed an ontology-based multi-dimension manufacturing feature model to facilitate the communication and collaboration between process planning and control, as well as to speed up the decision-making of intelligent agents.

Cluster 4: smart manufacturing , cloud computing, cloud manufacturing and sustainability

The term "cloud computing" refers to the distribution of applications and IT resources on-demand via the Internet with pricing based on consumption (the so-called "software as a service"). The cloud computing infrastructures are large data centres that allow users to access the resources (storage, applications, programs, services) they need, with the "pay-as-you-go" payment contract. This enables companies to reduce significantly their internal computing power and to buy resources accordingly to the specific current needs (http://www.infomart.it/cloud-computing). This makes companies more flexible and able to control fixed and variable costs.

Similarly, Cloud Manufacturing is the adoption of cloud computing for manufacturing purposes. Xu et al. (2012) described two degrees of the adoption of cloud computing in the manufacturing sector: 1. manufacturing with the partial adoption of cloud computing technologies or 2. cloud manufacturing i.e. a more pervasive use of cloud computing in all levels of the production and planning processes.

An example of the first level of adoption is represented by cases where demand planning and the organization of the supply chain are tied into a cloud-based system, allowing different parts of the organization to observe on what their sales teams are working.

As for the second level of adoption, a cloud manufacturing service platform performs searches, intelligent mapping, generation of recommendations, and execution of a service. The cloud users can request services ranging from production to product design, testing, management and all the other phases of the product life cycle. Important researches related to these themes were centred on the usability of cloud manufacturing environments and on the development of good user interfaces (Ren et al. 2015). Gaughran et al. (2007) studied how the more efficient use of resources, with the implementation of cloud manufacturing, has an impact on the industrial sustainability of the manufacturing process. They discussed the sustainability challenges of the industrial world, the related environmental and sustainable management issues, corporate responsibility and sources of competitive advantage.

Cluster 5: optimization, flexible manufacturing, scheduling and simulation

The growing need for increased customization of products and demand volatility together with sustainability requirements need efficient ways to design manufacturing configuration. The vast number of design configurations, however, affects the work of production planners who cannot longer rely on experience in order to plan the production.

In these settings, short-term scheduling is challenged by temporal machine availability, different processing time at parallel machines and dynamic job allocation. In their proposed framework, Ivanov et al. (2016) developed a dynamic model and optimization algorithm for short-term supply chain scheduling in smart factories. Moon et al. (2013) proposed the optimization of production scheduling with time and machine dependent electricity cost for industrial energy efficiency.

4.3.2. Kleinberg's Burst detection algorithm

The published literature in a particular research field can be seen as a sequence of topics that appear, grow in intensity for a period, and then fade away. The appearance of a topic in a document stream is signalled by a "burst of activity", with certain features rising sharply in frequency as the topic emerges. Kleinberg (2002) developed a formal approach for modelling "bursts", in such a way that they can be robustly and efficiently identified.

Kleinberg's approach is based on modelling the stream using an infinite state automaton, in which bursts appear naturally as state transitions; in some ways, it can be viewed as drawing an analogy with models from queueing theory for burst network traffic.

In the paper the Kleinberg's algorithm was applied to the author keywords of the papers retrieved using the keywords proposed in section 2 but ranging between 1995 and 2016. A wider time window was necessary to better detect the burst of keywords of the oldest papers in the set of the 462 papers considered. The author keywords of all the papers are extracted and pre-processed (normalized) using the Sci2 software to eliminate the stop-words, upper case, etc. with a text analysis algorithm. The results of the application of the burst detection algorithm are shown in Figure 8.

Figure 8. Burst detection Algorithm applied to normalized author keywords from 1995 to 2016.

The main bursts are related to sensors' technology and optimization (2009-2013) and to the IoT and the advent of the Cloud (2013-now). This means that the research interests around these themes increased in the last years. The results are in accordance with the results obtained from the GCS analyses and the main themes identified with VoS clustering. In fact, the use of RFID and wireless technology in manufacturing and the necessity of real-time production induce the necessity of new dynamic optimization tools to allocate job and machines, while the cloud manufacturing gives the possibility to access to a shared pool of manufacturing capabilities.

From the co-occurrence analysis of authors' keywords and the application of the burst detection algorithm, it seems that research has focused its interest on the Cloud concept, and specifically with reference to two different facets. One is represented by Cloud Computing (especially in terms of access to data on independent platforms and to external computing tools), and the other by Cloud Manufacturing (in terms of participative approach to the manufacturing process by all supply chain players through remote communications systems in the Cloud).
Second, Simulation stands out as another main research interest in terms of development of innovative dynamic optimization models based on Big Data and real time communication systems, as an evolution of the already existing traditional static/stochastic and time-definite optimization tools.
Third, another research trajectory regards the concept of the Industrial Internet of Things (or Internet of Manufacturing Things as named by some authors), where wireless communication systems and sensor networks empower intelligent objects and agents in the manufacturing process. This specifically seems to be proposed in terms of an evolution from the common and already known use of RFID systems as wireless technology in the manufacturing process. This evolution leads to the proposal of managerial and manufacturing models based on smart agent communities operating within factories – where the ontology of the communities is studied alongside the technical implications. This trajectory emerges also from the analysis of the author keywords: the burst detection algorithm showed that there was a burst of *wireless*, *rfid* and *optim* after 2008 and *smart*, *thing*, *cloud*, *monitor* started to appear afterwards, and specifically from 2012.

5. Discussion of the findings and research agenda

We combined the outcomes of the analyses to obtain an overall view of the state of the art and of the research trajectories of the knowledge on the Smart Factory concept. The identified research trajectories allow drawing some considerations about some directions in an agenda for future research.
First, the GCS analysis, the author keywords network analysis applying VoS clustering technique and the Kleinberg's burst detection algorithm seem to confirm research trajectories that recall and connect with some of the pillars of Industry 4.0 (The Boston Consulting Group, 2016). Specifically, researchers have worked on those pillars more connected to the development and adoption of software tools and of Cloud applications, i.e. the Cloud, Simulation, and The Industrial Internet of Things (e.g. Ren et al. 2015, Xu et al. 2012, Zhang et al. 2012). On the other hand, it seems that considerable changes in the manufacturing process through the adoption of new technologies in manufacturing plants have been quite overlooked. As suggested by Davis et al. (2012), a possible reason for this can be represented by the fact that the effort, in terms of necessary funding and in terms of radical changes in the manufacturing process, drives the current research and developments so far. Hence, initiatives that do not require considerable investments in machinery and manufacturing tools are more accessible to both large

and small-medium enterprises. Future research efforts are needed to investigate the reasons why, at the moment, it seems that the other pillars of Industry 4.0 are less popular and "connected" in the research community.

Second, and related to the previous point, our findings show that government and funding bodies can act both as relevant drivers and as barriers to the diffusion of the Smart Factory (Kagermann et al. 2013). This emerge as a common element to all geographical areas, as highlighted by our analyses on the three biggest connected components. Given the considerable role acknowledged by researchers to these stakeholders, it would be interesting to study the drivers and barriers that affect the implementation of the Smart Factory concept, and in particular, to investigate how governments and funding bodies can actually facilitate the development and implementation of the Smart Factory. This facilitation can include financial support, incentives schemes and regulatory frameworks (especially as far as policy makers are concerned).

Third, from our study, it seems also that organizational aspects of the implementation of developed software tools, Cloud applications and models for the Smart Factory have been rather neglected. In fact, our results show that papers have started to focus on managerial aspects and response to changing requirements of production but at a conceptual level only, e.g. integrating human and artificial agents in proposed conceptual frameworks (Kannengiesser et al. 2015, Kannengiesser and Muller 2013, Zamifirescu et al. 2013). Hence, an interesting consideration in terms of research agenda could be to deepen the study of the organizational impacts, change management and of the integration of the human resources in the development of the Smart Factory.

Fourth, our research highlighted the presence of models, frameworks and architectures related to the implementation of the Smart Factory (Wang et al. 2016b, Luo et al. 2015, Gaughran et al. 2007), along with high-level "landscape" analyses (Davis et al. 2012). It should be noted that these scientific contributions propose conceptual works and experiments, and rarely actual test-beds and lessons learned from the practice are described and discussed (Zuehlke, 2010). Hence, it would be opportune to explore the degree of adoption of the studied solutions in the industrial community to complement the results of our literature investigation. Surveys or case studies on companies would be beneficial in this sense, especially in different geographical contexts, to shed some light on the ways in which the Smart Factory is and can be implemented in the industrial community.

Fifth, and connected to the previous point, the reviewed literature highlighted the fact that the Smart Factory is a concept that spans beyond the boundaries of the focal company to embrace the extended supply chain (Davis et al. 2012). However, from our results it seems that studies focusing on the Smart Factory in the extended supply chain are missing, even if this appears to be a foundation of the pillar of Horizontal and Vertical Systems Integration within Industry 4.0. Therefore, this could lead to deepen the study of the necessity of a holistic approach to the Smart Factory within the supply chain through further investigations, which would hopefully provide also empirical evidence to complement the current dearth of field data.

Sixth, our review identified recent research trajectories towards the capturing and use of data and real time information through wireless technology, cloud computing and big data analytics (Wang et al. 2016a). The effective use and management of information and systems integration could be achieved only if suitable procedures secure the management and sharing of data and information across the chain of supply. In fact, it is well known that data and information management represents a source of risk in terms of security, and this is exacerbated in an environment such as the Smart Factory, which relies on the extensive use of large amounts of data and information. Literature seems to have addressed this topic in a very limited manner and consequently this opens further avenues for future research specifically focused on Cyber Risk and Security in the Smart Factory, given the relevance of security concerns for the development of a secure and integrated Smart Factory.

6. Conclusions

This study represents a first attempt to rationalize and systematize the existing body of scientific knowledge on the concept of the Smart Factory within the fourth industrial revolution. In doing this, different quantitative bibliometric analyses have been carried out, relying on algorithms and software tools that allowed for a dynamic representation of the flow of knowledge generation over time. In this way, we succeeded in providing the big picture of the knowledge on the subject under study, to identify some research trajectories and to generate an agenda for future research that encompasses the dynamic evolution of the subject matter.

In terms of theoretical implications, this study contributes to the current body of knowledge on the Smart Factory by analysing the evolution of this field of research, trends and emerging topics that are under-represented and require additional investigation. This paper provides an additional contribution: the described application to the concept of Smart Factory highlighted the distinctive features of the SLNA methodology that could be of benefit for application to other fields. Through it, researchers could gain a sense of the full picture of a field, or benefit from the decomposition of the citation network in its main components. This can help academics in further developing the body of knowledge of the field through the identification of the key issues, emerging trends and evolutionary trajectories.

This paper has practical implications too: it represents a first scoping study on a cutting-edge evolution of the world of manufacturing, it informs the industrial community about the current state of the art, and it identifies the directions in which the available knowledge has moved over the last few years. The dynamic analysis allowed highlighting the critical areas in the development of the field and it provides relevant information on the areas that companies, associations, policy makers and potentially providers of technology should focus on for enabling a real transition towards the large-scale implementation of the Smart Factory. This study contains also information that governments can use to draw programs and agendas for stimulating the evolution of the traditional manufacturing systems for better productivity and competitiveness of countries.

The methodology applied in this paper has also some limitations. The main criticism could be that taking into account the citations only may not be completely informative about the real contribution of a paper to the body of knowledge (Shema 2013). Another criticism is that citation data are retrieved from databases, such as WoS, that, although quite comprehensive, include only a fraction of scientific publications. A last issue often discussed is the so-called "Matthew effect", i.e. the rich get richer. This means that researchers tend to cite papers of well-known researchers that already received a high number of citations, because they tend to regard these papers as reliable sources of information due to their reputation and popularity.

Despite the discussed limitations, from a general viewpoint the interesting output of this study is not merely the visualisation of the citation network, but how SLNA can be exploited as a research tool to support dynamic analyses for drawing agendas that foster advances in the manufacturing world.

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Appendix

Main Path of the first biggest connected component (node number and reference). For the full list of references of the papers included in the first biggest connected component, please contact the authors.

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