ADDITIVE MANUFACTURING VS METAL ADDITIVE MANUFACTURING TECHNOLOGIES IN ENGINEERING: A BIBLIOMETRIC AND WEB INDICATOR ANALYSIS

Enara Zarrabeitia-Bilbao[1], Rosa María Rio-Belver[2], Izaskun Álvarez-Meaza[1], Gaizka Garechana-Anacabe[3]

[1]University of the Basque Country (UPV/EHU), Faculty of Engineering in Bilbao, Industrial Organization and Management Engineering Department, 1. 48013, 946014241, enara.zarrabeitia@ehu.eus
[2]University of the Basque Country (UPV/EHU), Faculty of Engineering in Vitoria-Gasteiz, Industrial Organization and Management Engineering Department, 01007
[3]University of the Basque Country (UPV/EHU), Faculty of Economics and Business in Bilbao (Elcano), Industrial Organization and Management Engineering Department, 48008

ESTUDIO COMPARATIVO DE LA LITERATURA APARECIDA SOBRE FABRICACIÓN ADITIVA NO METÁLICA Y FABRICACIÓN ADITIVA METÁLICA MEDIANTE UN ANÁLISIS BIBLIOMÉTRICO Y DE INDICADORES WEB

ABSTRACT:

Additive manufacturing (AM) is one of the main levers of change in the context of industry 4.0 and the metal additive manufacturing subgroup (MAM) is the most relevant in industry. This contribution analyses research trends and the academic, industrial and social impact of the research conducted in both areas. The articles published between 2010 and 2019 in the field of engineering research, with a total of 6,692 on AM technologies and 1,734 on MAM technologies, have been downloaded from the Web of Science database. In order to analyze who the main actors are and the academic impact, a bibliometric and web indicator analysis is applied. The social impact of the research carried out is visualized through twitter citations and, finally, its industrial impact is visualized through its connection with AM and MAM industrial patents. The study carried out allows us to conclude that the scientific development between AM and MAM is similar, however, the general public shows less interest in MAM. The transfer of knowledge to industry and the market is still low. The results obtained will offer advances in the knowledge and visualization of research production trends in AM and MAM technologies.

Keywords: Additive manufacturing, metal additive manufacturing, bibliometric analysis, web indicators, engineering

RESUMEN:

La fabricación aditiva (FA) es una de las principales palancas de cambio en el contexto de la industria 4.0 y, a su vez, el subgrupo de fabricación aditiva con metales (FAM) es el más relevante en la industria. Este trabajo de investigación, analiza las tendencias de la ciencia y el impacto académico, industrial y social de la investigación llevada a cabo en las dos áreas (FA y FAM). Para ello, se obtuvieron de la base de datos de la Web of Science (WoS) un total de 6.692 artículos sobre FA y 1.734 artículos sobre FAM, publicados entre 2010 y 2019, dentro del campo de investigación de la ingeniería. Para analizar quiénes son los principales actores y el impacto académico, se aplica un análisis bibliométrico y de indicadores web. El impacto social de los trabajos publicados se visualiza a través de las citas en twitter, y finalmente, el impacto industrial se visualiza a través de la conexión de los trabajos publicados con las patentes industriales en FA y FAM. El estudio realizado permite concluir que el desarrollo científico en la FA y la FAM es similar, pero el público general muestra menos interés por la FAM. Además, la transferencia de conocimientos a la industria y al mercado sigue siendo baja. Los resultados obtenidos permiten avanzar en el conocimiento y visualización de las tendencias de la producción científica sobre las tecnologías de FA y FAM.

Palabras clave: Fabricación aditiva, fabricación aditiva metálica, análisis bibliométrico, indicadores web, ingeniería

1. INTRODUCTION

Additive manufacturing (AM) is becoming one of the main levers of change in the context of industry 4.0. This industry segment is set to grow at approximately 12.5% in coming years, more than double its growth rate just a few years ago [1].

According to ISO/ASTM standards [2], AM is defined as "process of joining materials to make parts from 3D model data, usually layer upon layer, as opposed to subtractive manufacturing and formative manufacturing methodologies". Hence, additive manufacturing revolutionizes the way we approach the manufacture of prototypes and final parts, as the technique of adding material allows shapes and structures unthinkable in traditional processes of material subtraction.

Additive manufacturing technologies are continuously being redefined, reimagined and customized to a wide application spectrum such as automotive, aerospace, medical, consumer goods, and of course, also engineering [3], [4]. In just 30 years, numerous methods and technologies have been developed that allow the printing of different pieces of different material sizes and shapes, with great dimensional precision and mechanical qualities [5], [6]. However, although various AM processes or technologies have been introduced to the commercial market by industrial companies [7], the AM technologies currently with the highest industrial relevance are those included in the subgroup 'metal additive manufacturing' (MAM) [8].

Likewise, there are numerous studies on the characteristics, applications and processes of additive manufacturing and metal additive manufacturing, however, scientometric analyses are so far scarce [9].

Under such circumstances, the main aim of this study is to present an overall view of the trends and the impact of the research carried out on AM technologies in engineering, in general, and on MAM technologies in engineering, in particular; and compare both. The findings obtained will advance mapping the state of research into AM and MAM technologies.

2. RESEARCH METHODOLOGY

The primary goal of the study is a bibliometric and web indicator analysis to obtain the trends and impact of the research carried out on AM and MAM technologies in engineering; and compare both. Hence, figure 1 shows the procedure followed.

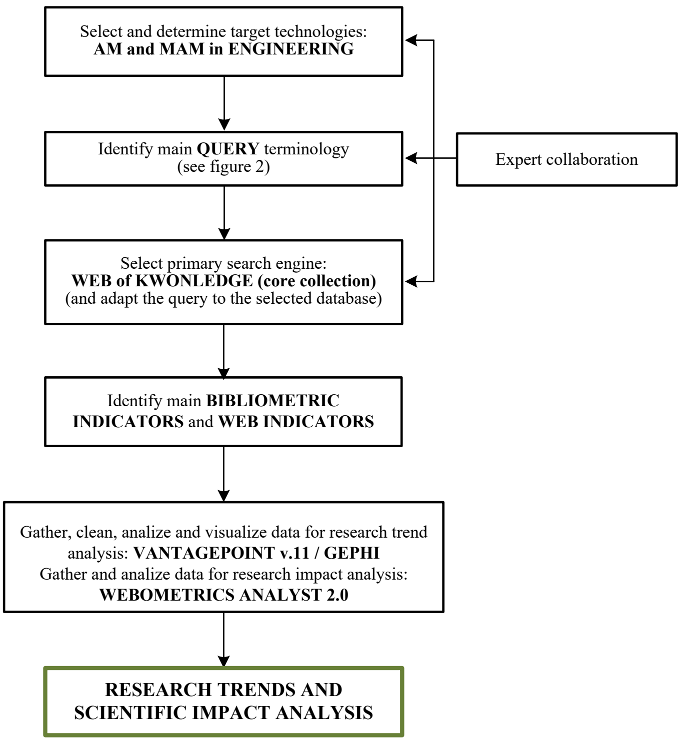


Fig. 1. Methodology workflow

Source: Own work based on [10]

Therefore, with the help of an expert in the field, the analysis began with the selection and determination of AM and MAM technologies in engineering as target technologies.

Afterwards, with the advice of the expert and based on previous studies into AM and MAM technologies [7], [8], [10]–[14], an adequate search query was built. For that, different terminology sets were delimited and defined: terms related to additive manufacturing, terms related to metal additive manufacturing and excluding terms. The terms related to additive manufacturing technologies and excluding terms were defined based on several previous works [10], [12], [13]. In order to build a proper MAM terminology, first of all, the most popular MAM processes and their synonyms were identified; and once these technologies were determined, the corresponding terms were defined [7], [8], [11], [14]–[16]. Thus, the main query terminology can be observed in figure 2.

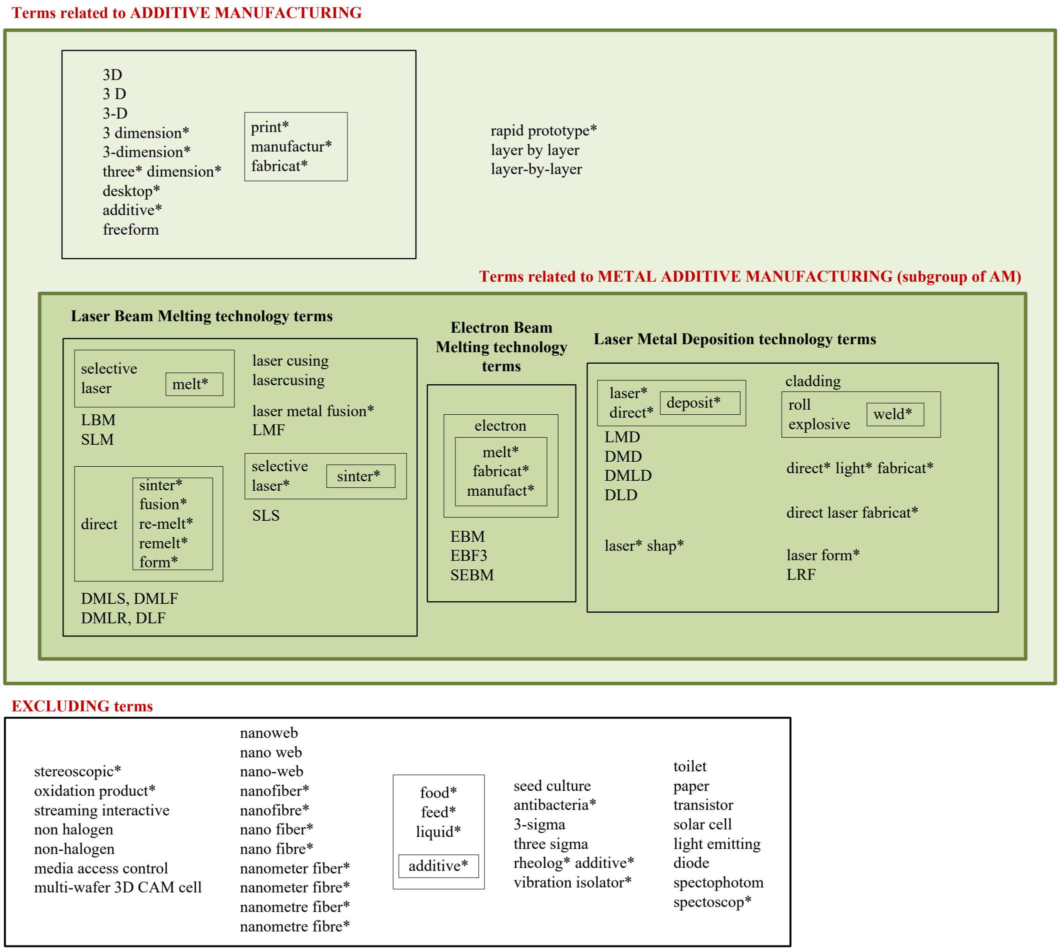


Fig. 2. Terminology related to AM and MAM technologies
Note: The (*) replaces zero characters or any combination of characters

Source: Own work based on [7], [8], [10]–[16]

The chosen primary search engine was the Web of Knowledge (WoS) Core Collection database, since it offers the most complete multidisciplinary information from over 21,100 high quality journals [17], [18] and allows the gathering of wide variety of variables to be analyzed; and the main query was adapted to be used in this database. In addition, in order to restrict research to the engineering scientific field, the research query was delimited to that research area.

Subsequently, once main bibliometric and web indicators were identified, the results obtained were gathered and analyzed making it possible to obtain the trends and the impact of the research carried out on AM technologies, in general, and in MAM technologies, in particular; and compare both.

The bibliometric indicator used to analyze research trend performance from the variables: publication year, country, author and author´s keywords; was the number of documents published [18]. The analysis of these variables will allow to know when, where, who and what is being researching in the field of interest. The software’s used to gather, clean, analyze and visualize articles data were VantagePoint [19] and Gephi [20]. For research trend analysis, the study period is set from 2010 to 2019 (October 16th).

With regard to the analysis of research impact, the bibliometric indicator used to analyze research academic impact performance was citation counts. Additionally, web indicators were also used to measure different impact types of publications. Specifically, academic, public engagement, plus industrial and commercial impact was measured from Mendeley readers, tweeters citations and Google Patents citations, respectively. The software used to gather and analyze web data was Webometrics Analyst [21] and for research impact analysis the study period is set from 2010 to 2017. In this case, it was decided that the last year analyzed would be 2017 with the aim of leaving a performance interval of more than one year until today, which allows the impact of more recently published articles to be analyzed.

The document type analyzed was articles because, on the one hand, when calculating field normalized indicators, it is best to analyze only one document type and this is normally the article document type [22] and, on the other hand, duplication of same research is avoided (e.g., conference papers and articles that are related to the same research).

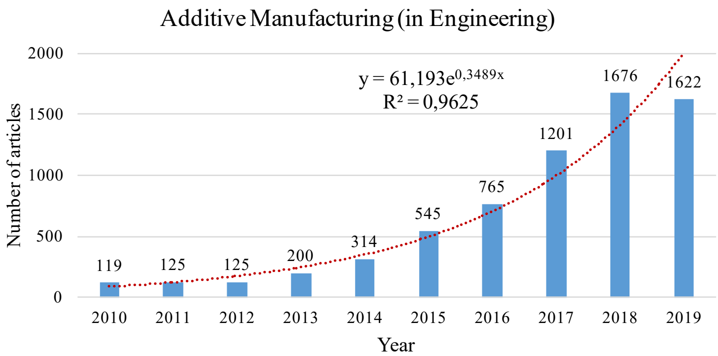
3. RESULTS AND DISCUSSION

The query used retrieved 6,692 journal articles about AM technologies in engineering, and 1,734 journal articles about MAM technologies in engineering, published from 2010 to 2019.

3.1. RESEARCH TRENDS ANALYSIS

3.1.1. Publication year analysis

AM and MAM in engineering have become technologies of growing academic interest, especially recent years. Figure 3 shows that the general trend of selected articles is in a phase of exponential growth; i.e., AM and MAM technologies in engineering are emerging research fronts [23].



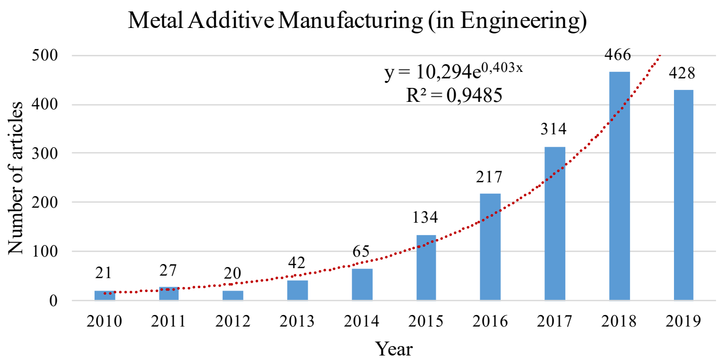


Fig. 3. General trend of selected articles from 2010 to 2019

3.1.2. Country analysis

On the one hand, authors from 97 countries published articles on AM technologies in engineering, and on the other hand, authors from 59 countries in MAM technologies in engineering. The two most prominent countries, by far, with the highest number of articles, both in AM technologies and in MAM technologies in engineering, are the USA and China, in that order (see table I). Furthermore, the most productive countries are practically the same in the case of both technologies.

3.1.3. Author analysis

Table I provides too an overview of the most productive authors. Among all the authors, the most notable being Cho Dong-Woo, from South Korea, in the case of AM; and Huang Weidong, from China, in the case of MAM.

<table>
<tr><th colspan="4">Additive Manufacturing (in Engineering)</th><th colspan="4">Metal Additive Manufacturing (in Engineering)</th></tr>
<tr><th colspan="8">MOST PRODUCTIVE COUNTRIES</th></tr>
<tr><th>Rank</th><th colspan="2">Country</th><th>Articles (%)</th><th>Rank</th><th colspan="2">Country</th><th>Articles (%)</th></tr>
<tr><td>1</td><td colspan="2">USA</td><td>2301 (34.38%)</td><td>1</td><td colspan="2">USA</td><td>557 (32.12%)</td></tr>
<tr><td>2</td><td colspan="2">China</td><td>1195 (17.86%)</td><td>2</td><td colspan="2">China</td><td>330 (19.03%)</td></tr>
<tr><td>3</td><td colspan="2">UK</td><td>575 (8.59%)</td><td>3</td><td colspan="2">Germany</td><td>179 (10.32%)</td></tr>
<tr><td>4</td><td colspan="2">Germany</td><td>498 (7.44%)</td><td>4</td><td colspan="2">UK</td><td>141 (8.13%)</td></tr>
<tr><td>5</td><td colspan="2">South Korea</td><td>371 (5.54%)</td><td>5</td><td colspan="2">Italy</td><td>96 (5.54%)</td></tr>
<tr><td>6</td><td colspan="2">Italy</td><td>291 (4.35%)</td><td>6</td><td colspan="2">Australia</td><td>81 (4.67%)</td></tr>
<tr><td>7</td><td colspan="2">Australia</td><td>277 (4.14%)</td><td>7</td><td colspan="2">Singapore</td><td>68 (3.92%)</td></tr>
<tr><td>8</td><td colspan="2">Canada</td><td>240 (3.59%)</td><td>8</td><td colspan="2">Canada</td><td>61 (3.52%)</td></tr>
<tr><td>9</td><td colspan="2">Japan</td><td>222 (3.32%)</td><td>9</td><td colspan="2">France</td><td>56 (3.23%)</td></tr>
<tr><td>10</td><td colspan="2">France</td><td>205 (3.06%)</td><td>9</td><td colspan="2">Japan</td><td>56 (3.23%)</td></tr>
<tr><th colspan="8">MOST PRODUCTIVE AUTHORS</th></tr>
<tr><th>Rank</th><th>Author</th><th>Country</th><th>Articles (%)</th><th>Rank</th><th>Author</th><th>Country</th><th>Articles (%)</th></tr>
<tr><td>1</td><td>Cho, Dong-Woo</td><td>South Korea</td><td>53 (0.79%)</td><td>1</td><td>Huang, Weidong</td><td>China</td><td>25 (1.44%)</td></tr>
<tr><td>2</td><td>Babu, Sudarsanam Suresh</td><td>USA</td><td>42 (0.63%)</td><td>2</td><td>Lin, Xin</td><td>China</td><td>24 (1.38%)</td></tr>
<tr><td>3</td><td>Chua, Chee Kai</td><td>Singapore</td><td>36 (0.54%)</td><td>3</td><td>Wicker, Ryan B</td><td>USA</td><td>22 (1.27%)</td></tr>
<tr><td>4</td><td>Huang, Weidong</td><td>China</td><td>30 (0.45%)</td><td>4</td><td>Qian, Ma</td><td>Australia</td><td>21 (1.21%)</td></tr>
<tr><td>4</td><td>Wicker, Ryan B</td><td>USA</td><td>30 (0.45%)</td><td>5</td><td>Gu, Dongdong</td><td>China</td><td>19 (1.10%)</td></tr>
<tr><td>5</td><td>Lin, Xin</td><td>China</td><td>29 (0.43%)</td><td>5</td><td>Kruth, Jean-Pierre</td><td>Belgium</td><td>19 (1.10%)</td></tr>
<tr><td>6</td><td>Toyserkani, Ehsan</td><td>Canada</td><td>28 (0.42%)</td><td>5</td><td>Niendorf, Thomas</td><td>Germany</td><td>19 (1.10%)</td></tr>
<tr><td>7</td><td>Shamsaei, Nima</td><td>USA</td><td>25 (0.37%)</td><td>6</td><td>Koerner, Carolin</td><td>Germany</td><td>18 (1.04%)</td></tr>
<tr><td>8</td><td>Qian, Ma</td><td>Australia</td><td>23 (0.34%)</td><td>6</td><td>Shamsaei, Nima</td><td>USA</td><td>18 (1.04%)</td></tr>
<tr><td>9</td><td>Choi, Jae Won</td><td>USA</td><td>22 (0.33%)</td><td>7</td><td>Murr, Lawrence E</td><td>USA</td><td>17 (0.98%)</td></tr>
</table>

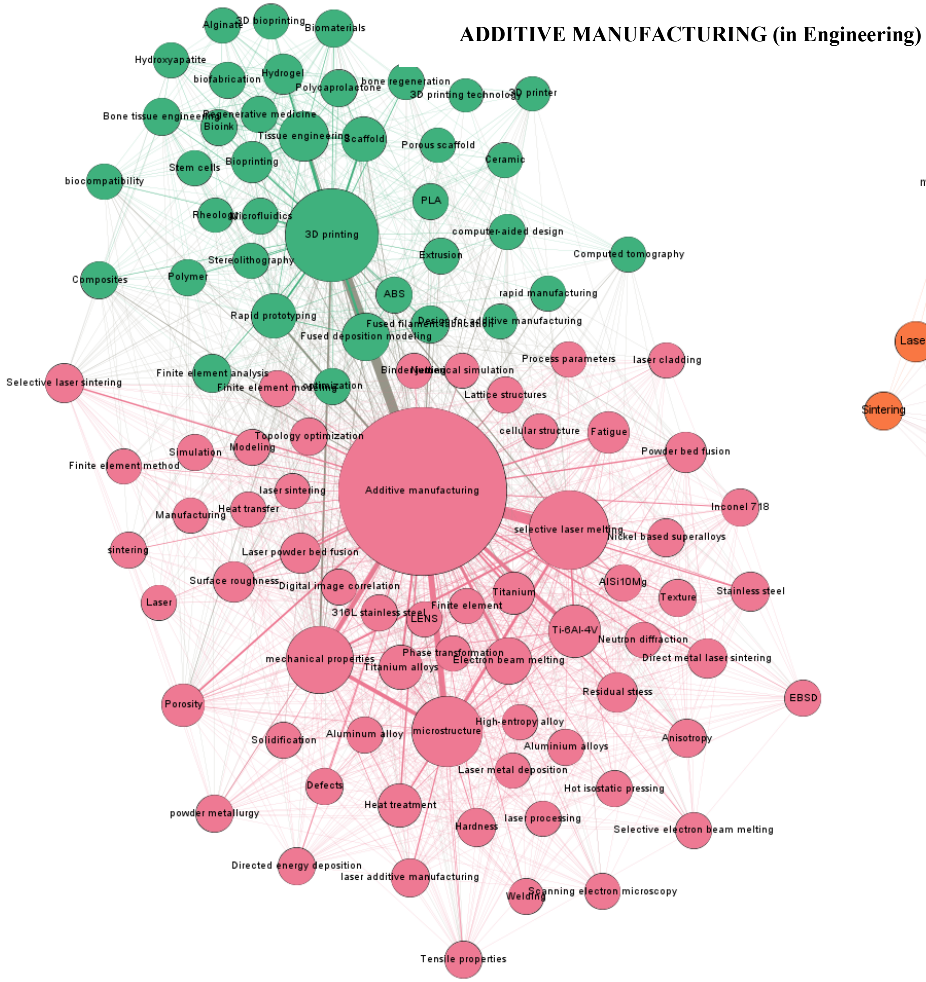
Table I. The most productive countries and authors

3.1.5. Keywords analysis

The author´s keywords (see figure 4) show the knowledge hotspots of the articles gathered and analysis of these author´s keywords makes it possible to identify key research points in AM and MAM technologies in engineering research fields.

Concretely, with regard to the AM technologies keyword network, the clustering of the main keywords (top 100) defines two clusters. The first, and the largest (in pink), is formed around the "Additive Manufacturing" term and it is related to metal additive manufacturing technologies, metals and alloys, among others. The second (in green) is formed around the "3D printing" term and is related to other non-metallic technologies and materials, plus medicine and bioprinting, among others. Therefore, the relevance, to a large extent, of MAM and within AM can be seen, without overlooking the biomedical area.

As far as the MAM technologies keyword network is concerned, the clustering of the main keywords (top 100) defines three clusters. However, it can be said that there is only one real cluster (in purple), since the other two are practically inexistent (the orange one related to general concepts and the green one related to medicine and bioprinting).



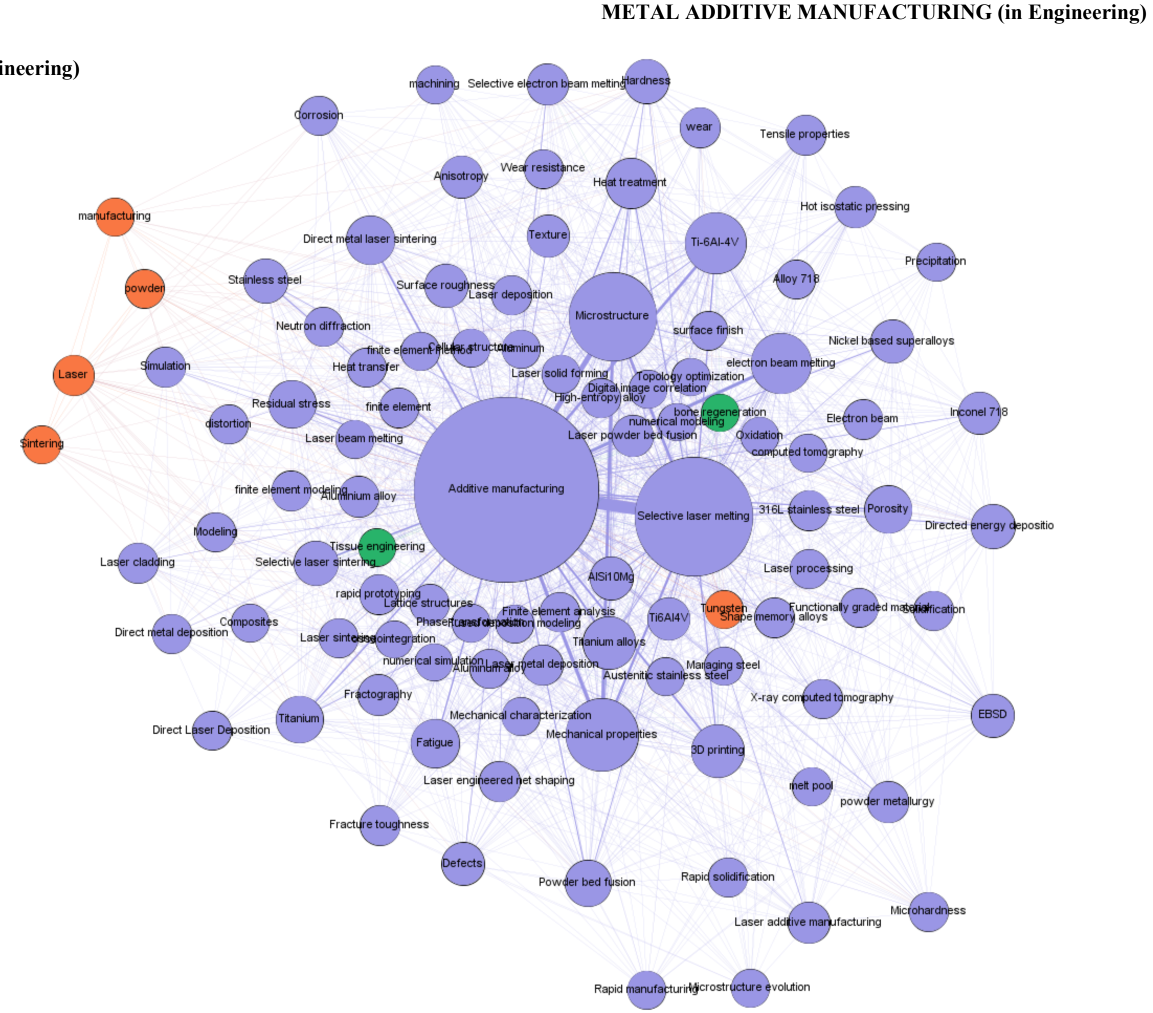


Fig. 4. Networks of top 100 author´s keywords co-occurrence on AM and MAM in engineering

3.2. RESEARCH IMPACT ANALYSIS

In order to carry out the research impact analysis of AM and MAM articles published in engineering research field, and compare both, different impact indicators were analyzed. Therefore, as shown in table II, the arithmetic means of the counts and, with 95% confidence intervals, the proportion of articles with at least one count of each indicator, the Mean Normalized Log-transformed Citation Score (MNLCS)[1] and the Equalized Mean-based Normalized Proportion Cited (EMNPC)[2] are given [24].

3.2.1. Academic impact

As expected, the most read and cited articles, in general, are those that have been published earlier, i.e., there is relation between the publication date and number of readers and number of citations. Besides, practically all articles have been read or cited at least once.

As for the comparison of both technologies, the MNLCS values are higher than 1 for MAM, which indicates that the Mendeley readers and the citation counts for MAM tend to be above the world average (AM average). In addition, the EMLCS values are higher than 1 for all analyzed years in the case of citation counts and higher than 1 for practically all analyzed years in the case of Mendeley readers, hence, MAM articles are above the world average for the non-zero cited proportion too.

3.2.2. Attention/interest or public engagement impact

Tweets about research on AM and MAM in engineering are difficult to collect from Twitter; however, in line with the fact that people are increasingly far more engaged with social media year by year [25], in this case too, Twitter citations are increasing year after year.

Half the tweets to academic papers are made by non-academics, indicating a wider public interest [26]. In this instance, as expected, for practically all years the general public tweets more about AM technologies, being more generic, than MAM technologies.

3.2.3. Industrial and commercial impact

As expected, the most cited articles on AM technologies in patents, in general, are those that have been published earlier, rather surprisingly the same does not occur with MAM technologies. With the latter, there is no relation between the publication date and cited articles in patents.

In this case, there is no clear trend as far as the impact predominance of both technologies in terms of citations and non-zero proportion. In addition, citations in Google Patents are quite scarce in both technologies.

[1] $\mathrm{MNLCS} = \frac{\text{Average number of log-transformed citations for the group}}{\text{Average number of log-transformed citations for the corresponding world set}}$

[2] $\mathrm{EMNPC} = \frac{\text{Proportion of cited articles for a group}}{\text{Proportion of cited articles for the corresponding world sets}}$

ACADEMIC IMPACT			
MENDELEY READERS COUNTS			
Indicators	**Year**	**AM**	**MAM**
Arithmetic mean of raw data	2010	74.084034	**181.809524**
	2011	69.048000	**119.629630**
	2012	65.424000	**128.100000**
	2013	75.200000	**113.357143**
	2014	77.340764	**106.569231**
	2015	65.631193	**103.022388**
	2016	60.084967	**80.829493**
	2017	46.253122	**63.910828**
Proportion (95%CI) non-zero	2010	0.873950 (0.802408, 0.922103)	**0.904762 (0.710859, 0.973481)**
	2011	0.968000 (0.920606, 0.987487)	**1.000000 (0.875445, 1.000000)**
	2012	0.936000 (0.878785, 0.967216)	**0.950000 (0.763869, 0.991119)**
	2013	**0.965000 (0.929529, 0.982944)**	0.952381 (0.842101, 0.986842)
	2014	0.971338 (0.946433, 0.984849)	**0.984615 (0.917867, 0.997279)**
	2015	0.915596 (0.889249, 0.936126)	**0.940299 (0.886615, 0.969441)**
	2016	**0.935948 (0.916326, 0.951213)**	0.917051 (0.872704, 0.946888)
	2017	0.954205 (0.940865, 0.964649)	**0.964968 (0.938369, 0.980328)**
MNLCS - mean (95%CI) of world normalized ln(1+raw data)	2010	1.000000 (0.871638, 1.147266)	**1.229187 (0.924096, 1.557514)**
	2011	1.000000 (0.911915, 1.096593)	**1.200082 (1.050205, 1.360169)**
	2012	1.000000 (0.892204, 1.120820)	**1.244453 (1.029493, 1.475620)**
	2013	1.000000 (0.927356, 1.078334)	**1.138332 (0.999126, 1.284017)**
	2014	1.000000 (0.943262, 1.060150)	**1.135592 (1.041172, 1.233887)**
	2015	1.000000 (0.948351, 1.054462)	**1.167059 (1.082310, 1.255159)**
	2016	1.000000 (0.960218, 1.041430)	**1.085339 (1.020363, 1.152141)**
	2017	1.000000 (0.968557, 1.032463)	**1.138301 (1.089819, 1.187946)**
EMNPC (NPC) - world normalized proportion (95%CI) cited (non-zero)	2010	1.000000 (0.909692, 1.099273)	**1.035256 (0.903435, 1.186312)**
	2011	1.000000 (0.958795, 1.042976)	**1.033058 (NeuN[3], NeuN)**
	2012	1.000000 (0.939286, 1.064639)	**1.014957 (0.934131, 1.102777)**
	2013	**1.000000 (0.964715, 1.036575)**	0.986923 (0.926198, 1.051629)
	2014	1.000000 (0.974246, 1.026435)	**1.013670 (0.985426, 1.042723)**
	2015	1.000000 (0.964800, 1.036484)	**1.026979 (0.978466, 1.077898)**
	2016	**1.000000 (0.974264, 1.026416)**	0.979810 (0.938096, 1.023378)
	2017	1.000000 (0.982713, 1.017591)	**1.011280 (0.987313, 1.035829)**
CITATION COUNTS FOR INDIVIDUAL SETS OF ARTICLES			
Indicators	**Year**	**AM**	**MAM**
Arithmetic mean of raw data	2010	48.042017	**108.857143**
	2011	36.616000	**55.259259**
	2012	36.008000	**62.350000**
	2013	34.715000	**54.023810**
	2014	31.656051	**41.276923**
	2015	23.750459	**38.007463**
	2016	19.803922	**28.990783**
	2017	10.351374	**15.025478**
Proportion (95%CI) non-zero	2010	0.915966 (0.852202, 0.953715)	**0.952381 (0.773306, 0.991544)**
	2011	0.968000 (0.920606, 0.987487)	**1.000000 (0.875445, 1.000000)**
	2012	0.960000 (0.909774, 0.982795)	**1.000000 (0.838875, 1.000000)**
	2013	0.960000 (0.923068, 0.979594)	**1.000000 (0.916201, 1.000000)**
	2014	0.949045 (0.918840. 0.968395)	**0.969231 (0.894573, 0.991521)**
	2015	0.926606 (0.901599, 0.945640)	**0.977612 (0.936246, 0.992357)**
	2016	0.930719 (0.910489, 0.946645)	**0.958525 (0.923070, 0.978029)**
	2017	0.882598 (0.863161, 0.899595)	**0.936306 (0.903672, 0.958393)**
MNLCS - mean (95%CI) of world normalized ln(1+raw data)	2010	1.000000 (0.858673, 1.164588)	**1.216604 (0.875300, 1.586208)**
	2011	1.000000 (0.897573, 1.114116)	**1.189918 (1.023275, 1.370470)**
	2012	1.000000 (0.884333, 1.130796)	**1.188360 (0.957595, 1.437104)**
	2013	1.000000 (0.915987, 1.091718)	**1.229755 (1.093503, 1.375482)**
	2014	1.000000 (0.925552, 1.080437)	**1.119305 (0.988206, 1.257106)**
	2015	1.000000 (0.941141, 1.062540)	**1.210925 (1.114060, 1.312340)**
	2016	1.000000 (0.951868, 1.050566)	**1.145943 (1.069617, 1.225116)**
	2017	1.000000 (0.955382, 1.046702)	**1.209644 (1.137730, 1.284078)**
EMNPC (NPC) - world normalized proportion (95%CI) cited (non-zero)	2010	1.000000 (0.927890, 1.077714)	**1.039755 (0.954819, 1.132247)**
	2011	1.000000 (0.958795, 1.042976)	**1.033058 (NeuN, NeuN)**
	2012	1.000000 (0.953220, 1.049076)	**1.041667 (NeuN, NeuN)**
	2013	1.000000 (0.962052, 1.039445)	**1.041667 (NeuN, NeuN)**
	2014	1.000000 (0.964983, 1.036287)	**1.021270 (0.976263, 1.068352)**
	2015	1.000000 (0.967355, 1.033747)	**1.055047 (1.020693, 1.090556)**
	2016	1.000000 (0.973163, 1.027577)	**1.029876 (0.996404, 1.064473)**
	2017	1.000000 (0.971308, 1.029540)	**1.060852 (1.024236, 1.098777)**

PUBLIC ENGAGEMENT IMPACT			
TWEETERS CITATIONS COUNTS			
Indicators	**Year**	**AM**	**MAM**
Arithmetic mean of raw data	2010	**0.018018**	0.000000

[3] NeuN: The confidence limits are impossible to calculate, therefore, are considered infinite.

	2011	0.067227	**0.259259**
	2012	**0.111111**	0.095238
	2013	**1.200000**	0.023810
	2014	**0.650000**	0.203125
	2015	**0.768173**	0.232558
	2016	**1.213205**	0.357843
	2017	**1.146037**	0.545752
Proportion (95%CI) non-zero	2010	**0.018018 (0.004955, 0.063326)**	0.000000 (0.000000, 0.154639)
	2011	0.025210 (0.008610, 0.071505)	**0.074074 (0.020555, 0.233696)**
	2012	0.068376 (0.035052, 0.129142)	**0.095238 (0.026519, 0.289141)**
	2013	**0.142105 (0.099536, 0.198860)**	0.023810 (0.004215, 0.123212)
	2014	**0.196667 (0.155645, 0.245359)**	0.078125 (0.033831, 0.170195)
	2015	**0.292731 (0.254872, 0.333695)**	0.100775 (0.059843, 0.164796)
	2016	**0.324622 (0.291584, 0.359503)**	0.171569 (0.126027, 0.229251)
	2017	**0.306322 (0.280060, 0.333905)**	0.186275 (0.146639, 0.233689)
MNLCS - mean (95%CI) of world normalized ln(1+raw data)	2010	**1.000000 (NeuN, NeuN)**	0.000000 (NeuN, NeuN)
	2011	1.000000 (NeuN, NeuN)	**3.490602 (NeuN, NeuN)**
	2012	1.000000 (0.245185, 4.078545)	**1.079533 (-0.426424, 5.094032)**
	2013	**1.000000 (0.502423, 1.990356)**	0.081518 (-0.084169, 0.287374)
	2014	**1.000000 (0.679366, 1.471961)**	0.395849 (0.041745, 0.809856)
	2015	**1.000000 (0.796816, 1.254995)**	0.351484 (0.152430, 0.569132)
	2016	**1.000000 (0.838964, 1.191946)**	0.456315 (0.301263, 0.625766)
	2017	**1.000000 (0.862554, 1.159347)**	0.543096 (0.390461, 0.707627)
EMNPC (NPC) - world normalized proportion (95%CI) cited (non-zero)	2010	**1.000000 (0.176720, 5.658683)**	0.000000 (0.000000, 0.000000)
	2011	1.000000 (0.232319, 4.304422)	**2.938272 (0.612329, 14.099343)**
	2012	1.000000 (0.400302, 2.498115)	**1.392857 (0.367845, 5.274098)**
	2013	**1.000000 (0.613351, 1.630387)**	0.167549 (0.033523, 0.837402)
	2014	**1.000000 (0.724889, 1.379522)**	0.397246 (0.173085, 0.911715)
	2015	**1.000000 (0.826532, 1.209875)**	0.344259 (0.204174, 0.580456)
	2016	**1.000000 (0.862391, 1.159567)**	0.528519 (0.385028, 0.725485)
	2017	**1.000000 (0.883080, 1.132400)**	0.608100 (0.474078, 0.780009)
INDUSTRIAL AND COMMERCIAL IMPACT			
GOOGLE PATENTS CITATION COUNTS			
Indicators	**Year**	**AM**	**MAM**
Arithmetic mean (unique domains)	2010	0.109244	**0.142857**
	2011	**0.064000**	0.037037
	2012	**0.072000**	0.050000
	2013	0.060606	**0.075000**
	2014	**0.060510**	0.030769
	2015	0.049541	**0.059701**
	2016	0.027451	**0.046083**
	2017	**0.015063**	0.012821
Proportion non-zero (95%CI)	2010	0.109244 (0.064962, 0.177964)	**0.142857 (0.049810, 0.346361)**
	2011	**0.064000 (0.032784, 0.121215)**	0.037037 (0.006568, 0.182835)
	2012	**0.072000 (0.038339, 0.131183)**	0.050000 (0.008881, 0.236131)
	2013	0.060606 (0.035006, 0.102932)	**0.075000 (0.025836, 0.198642)**
	2014	**0.060510 (0.039076, 0.092566)**	0.030769 (0.008479, 0.105427)
	2015	0.049541 (0.034268, 0.071120)	**0.059701 (0.030559, 0.113385)**
	2016	0.027451 (0.018024, 0.041600)	**0.046083 (0.025221, 0.082736)**
	2017	**0.015063 (0.009549, 0.023684)**	0.012821 (0.004997, 0.032495)
MNLCS - mean (95%CI) of world normalized log (1_unique domains)	2010	1.000000 (0.432852, 2.310261)	**1.307692 (-0.111679, 3.698825)**
	2011	**1.000000 (0.291676, 3.428465)**	0.578704 (-0.649234, 2.802094)
	2012	**1.000000 (0.328153, 3.047356)**	0.694444 (-0.764618, 3.108722)
	2013	1.000000 (0.401514, 2.490573)	**1.237500 (-0.142679, 3.721636)**
	2014	**1.000000 (0.505809, 1.977031)**	0.508502 (-0.203533, 1.466062)
	2015	1.000000 (0.575348, 1.738078)	**1.205086 (0.372389, 2.424478)**
	2016	1.000000 (0.523576, 1.909942)	**1.678736 (0.616693, 3.486786)**
	2017	**1.000000 (0.489351, 2.043525)**	0.851140 (0.021000, 2.134831)
EMNPC - world normalized proportion non-zero (95%CI) [i.e. risk ratio]	2010	1.000000 (0.491491, 2.034625)	**1.307692 (0.443983, 3.851634)**
	2011	**1.000000 (0.399385, 2.503848)**	0.578704 (0.107296, 3.121257)
	2012	**1.000000 (0.421285, 2.373688)**	0.694444 (0.132562, 3.637935)
	2013	1.000000 (0.468211, 2.135787)	**1.237500 (0.397547, 3.852136)**
	2014	**1.000000 (0.544500, 1.836549)**	0.508502 (0.140076, 1.845953)
	2015	1.000000 (0.597468, 1.673731)	**1.205086 (0.571756, 2.539949)**
	2016	1.000000 (0.554703, 1.802768)	**1.678736 (0.815204, 3.456994)**
	2017	**1.000000 (0.527596, 1.895390)**	0.851140 (0.306110, 2.366597)

Table II. Academic impact, public engagement impact, and industrial and commercial impact of AM and MAM technologies in engineering

4. CONCLUSIONS AND FUTURE LINES OF RESEARCH

Expectations for additive manufacturing technologies are very high, as additive manufacturing is so much more than a technological transition that it could change user practices and institutional and business frameworks. In this context, metal additive manufacturing has evolved rapidly in recent years and, despite being a young technology, has a lot of potential, due to interest in metals at industrial level for their mechanical, electrical, chemical, etc. properties.

Research trends are similar for AM and MAM technologies in engineering. AM and MAM in engineering are emerging research fronts, which present significant research opportunities in both areas. The USA and China are the main actors in both areas.

The key elements of research within additive manufacturing show the interest and importance of metal treatment within this field. Concretely, the two main research areas observed are: biomedicine (and related materials, plus polymers and techniques); and metal additive manufacturing.

Although research tendencies are similar for both AM and MAM technologies in engineering, scientific studies into MAM technologies have higher academic impact. However, the general public shows less interest in MAM, i.e., it has less public engagement impact. On the other, in general there is little transfer of knowledge to industry or market. In both cases, citations in Google Patents for AM and MAM are scarce, consequently industrial and commercial impact is low.

Future research should include new fields of research within additive manufacturing, as well as new analysis indicators and variables. In addition, the opinion of experts in the field would be of great value to complete these works.

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