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Real-Time Monitoring of FDM 3D Printer for Fault Detection Using Machine Learning: A Bibliometric Study

Vaibhav Kisan Kadam
Symbiosis International University, vaibhavkadam439@gmail.com

Satish Kumar
Symbiosis International University, satishkumar.vc@gmail.com

Arunkumar Bongale
Symbiosis Institute of Technology (SIT), Symbiosis International (Deemed) University, Pune, arunbongale1980@gmail.com

Real-Time Monitoring of FDM 3D Printer for Fault Detection Using Machine Learning: A Bibliometric Study

Vaibhav Kadam[1], Satish Kumar[1]*, Arunkumar Bongale[1]

Department of Mechanical Engineering, Symbiosis Institute of Technology (SIT),

Symbiosis International (Deemed) University, Pune, India.

Abstract

Additive Manufacturing has a wide application range, including healthcare, Fashion, Manufacturing, Prototypes, Tooling, etc. AM techniques are subjected to various defects that may be printing defects or anomalies in the machine. There is a gap between current AM techniques and smart manufacturing since current AM lacks in build sensors necessary for process monitoring and fault detection. Both of these issues can be solved by incorporating real-time monitoring into AM. So the study is carried out to identify recent work done in AM to improve the current system. For this bibliometric study, the Scopus database is used; the research is kept limited to the year 2010-2021 and English language for recent trend analysis. A total of 1483 documents are analyzed based on author co-authors, keyword, geographical area, funding sponsor, affiliation, subject area, source title, and citation count. The study is also focused on ML's use for fault detection in AM, types of monitoring methods, challenges, and future direction of AM in smart manufacturing.

Keywords

Additive Manufacturing, Fault Detection, Machine Learning, Real-Time Monitoring, Fused Deposition Modelling

1. Introduction

1.1 Additive Manufacturing (AM)

Additive manufacturing (AM) is a process that forms a 3D object which is created by layer by layer deposition of material. For the creation of 3D printed objects, additive manufacturing uses cad software using which virtual model is built and then inputted into a machine [1]. In recent years, AM has been widely used to manufacture various components in healthcare, fashion design, fabrication of physical manufacturing prototypes, etc. [2]. "There are several types of AM processes which includes fused deposition modeling (FDM), stereolithography (SLA), digital light processing (DLP), selective laser sintering (SLS), multi-jet fusion (MJF), polyjet, electron beam melting (EBM), direct metal laser sintering (DMLS)" [3]. Out of these AM processes, Fused Deposition Modelling (FDM) is widely used because of low-cost material and variety of material availability. The material used in the FDM process is a polymer which is in the form of long cylindrical wire. Fig 1 shows the general procedure of 3D printing. The process starts with the cad model generation, which is inputted into the machine for parameter selection like printing speed, temperature, pattern, etc. After selecting printing parameters, G & M codes are form and printing of part takes place,

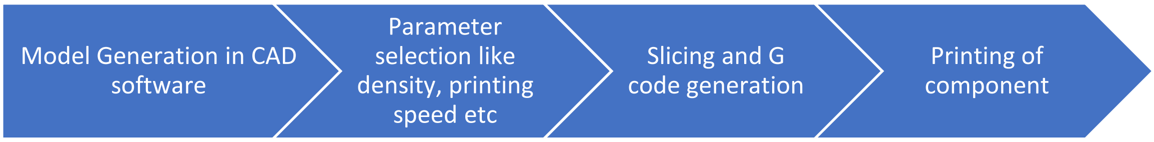

Fig 1: General process of 3D printing

AM is a crucial component in today's manufacturing. Due to its vast variety of product development and flexible adaption to various manufacturing components, it is an essential component in the smart manufacturing system. AM system can quickly adapt to the production of new products and change demands, which can disrupt traditional supply change.

Even with the wide application of AM, its use is limited due to various defects involved in printed components. Due to poor quality rates and multiple defects, the adoption of AM is hampered.

1.2 Common Defects in 3d Printed Components

FDM 3D printers are subjected to various types of defects. Common defects are that occur are shown in fig 2.

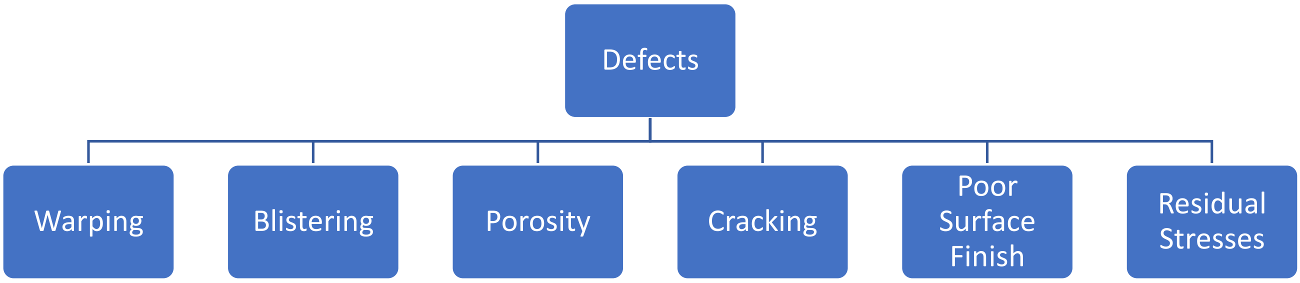

Fig 2: Defects in 3D Printed Components

a) Warping – In this defect, the printed part swells upward, which can be caused due to improper cooling of the printed component or materials used in the process [4].

b) Blistering – In this type of defect lower layer of the printed component swells outward. This is due to improper cooling of the lower layer, which causes swelling of material because of the upper layers' weights.

c) Porosity – In this defect, very small air bubbles or cavities form in the printed component during the printing process. It may be because of the improper printing process or material used in the process. This defect reduces the density of printed parts, leading to failure of components [5].

d) Cracking – Small crack generation may occur due to small cavities, stress formation, or uneven heating or cooling of a particular area. This leads to the formation of big cracks and eventually failure of components [5].

e) Poor Surface Finish – This problem arises mainly in FDM 3D printers because of the technique and material used in the process. Because of which parts produced by the FDM process often require post-processing [6].

f) Residual Stresses – Residual stresses generate because of rapid heating or cooling of the material, leading to expansion or contraction of the material. When residual stress exceeds the limit of tensile strength, it can lead to the formation of cracks or defects like the warpage [7].

For various FDM printers, there is a lack of inbuilt sensors and feedback systems. Sensors are available in FDM printers but only for features like nozzle and build platform. Commercial FDM printers do not monitor the printing process if it goes as expected. For example, if some error occurs, if printed components get off the build platform due to lack of adhesion, or any other kind of error occurs, the printing process will continue, leading to wastage of material and time [8]. Future AM machine should be smart machines which should be able to perform self-monitoring, self-calibration, and self-diagnosis in real-time. The gap between currently available AM machine and smart manufacturing machines need to be bridge for better production rate, more accuracy, less wastage [9]. This can be possible by real-time monitoring of the printing process.

1.3 Real-Time Monitoring

Real-time data monitoring is the continuous feeding of information to keep the system aware and updated [10]. It involves collecting data from production site and storing and processing the data for anomaly detection, system performance, and resolving issues involved. Real-time monitoring provides zero or low latency streaming data continuously directly to the desired system from which the administrator can monitor the system and, if some problem arises, give feedback to the system [11]. Data feedback can be delivered quickly to the staff or to the automated system for mitigation by real-time monitoring. By monitoring real-time data periodically with respect to time, one can calculate system efficiency and predict trends and performance. Due to which it enables organizations to optimize production processes for better efficiency and performance with less downtime.

Nowadays, many industries incorporate real-time monitoring for various purposes like a routine checkup for maintenance, plant monitoring, etc. Due to the development of high accuracy sensors, optical fiber lines, cloud storage, and low-cost IoT sensors, real-time monitoring became more feasible. For monitoring of the machine, process, etc., many sensors are required, and the number of sensors increases depending upon system complexity. The sensor's position is also a very important parameter to consider since it affects data collection accuracy. Sometimes, the system is very complex that it is very difficult to find the perfect position of sensors for monitoring. We need to identify defects in an earlier stage in production or before it happens; that type of monitoring is called condition monitoring.

Condition Monitoring –
It monitors processes and parameters and can predict if process will fail or some error will occur. ML is widely used in this type of monitoring since it provides various algorithms that can detect almost accurately anomaly that is about to happen [12]. By comparing previous data and analyzing patterns, it can identify the component's condition and predict impeding faults [13].

Benefits of Real-Time Monitoring

1) Collecting real-time data enables an organization to make better optimization of the system. It helps in analyzing trends and patterns and current events in the environment.
2) Organizations can track data for scheduling maintenance effectively, thereby reducing downtime in the production process.
3) Real-time monitoring and anomaly detection are possible with the help of real-time data.
4) Improves organization productivity and reduces wastage and downtime.

Real-time monitoring provides the data which needs to be processed. ML provides various techniques and algorithms that can be used to process, classify, and monitor systems for fault detection.

1.4 Use of ML for Fault Detection in 3D Printer

Machine learning is a computational technique that gives results using various algorithms and uses experience to improve performance, where experience means data available for training [14]. It is a subset of Artificial Intelligence (AI) which uses various algorithms for computation to train data and identify patterns, objects, etc. There are four types of ML as follows

- Supervised Learning – In this, you have two parameters input and output. Various algorithms are used to extract features from input, which is labeled to predict desired output and map input to output relationship. In this data labeling is done by the operator [15].

- Unsupervised Learning – It differs from supervised learning in one major aspect that is the labeling of data; here model itself identifies features, patterns that are categorized accordingly using self-learning. In this, the process takes place without human interference [15].
- Semi-supervised Learning – It is a mixture of both supervised and unsupervised learning in which both labeled and non-labeled data is provided to the model. It is more accurate than unsupervised learning since some amount of labeled data is provided by the operator and less costly than supervised learning. It is used when the labeling of large data is not possible or very expensive [16].
- Reinforced Learning – It differs from supervised learning in the sense of labeled data. Here labeled data is not provided, and the model itself learns from environment and experience and produces good and bad results [16].

With help of real-time monitoring, the printing process can be monitor for fault detection. Fault detection can be carried out with the help of various ML algorithms. The process flowchart for anomaly detection in 3D printing is shown in fig 3.

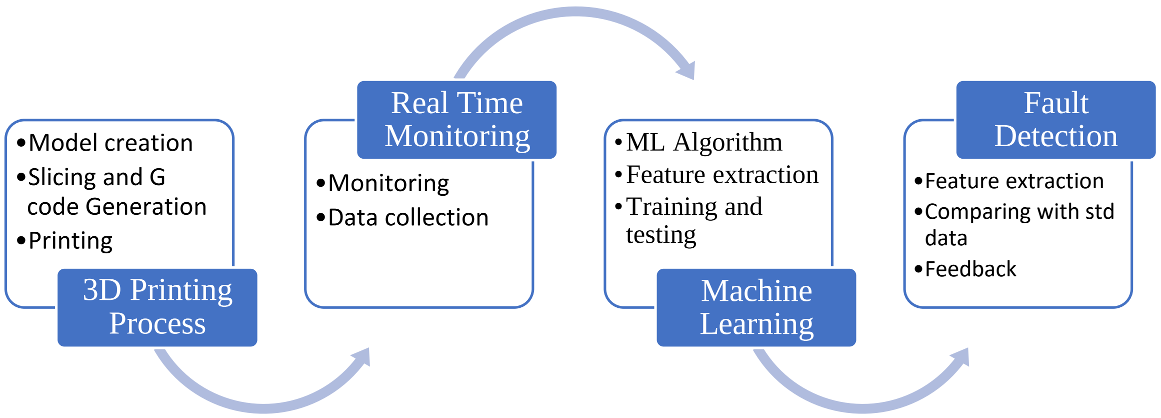

Fig 3: Process Flow Chart for Anomaly Detection

FDM 3D printers are subjected to various defects which affect product quality in term of manufacturing cost, the time required for production, material utilization. With the help of real-time monitoring and ML, various printing process faults can be identified in the earliest stage, which can reduce further wastage of time, money, and material.

2. Methodology

Bibliometric analysis is a quantitative technique used to analyze research documents for trends, future scope, literature gaps, etc. This bibliometric analysis includes subject area, author name, type of document, document count, source title, keyword, affiliation, year of publication, geographical location for trend analysis, and for finding gaps in the literature. For this analysis, the Scopus database is used since it has vast numbers of documents in various research areas like mechanical, computer, agriculture, etc. which makes comparative study easy. The objectives of this bibliometric study are

- To find out trends and gaps in the literature.
- To find year-wise publication count to analyze recent documents.
- To find geometrical area-wise development in additive manufacturing.
- To study the total number of cited documents.

2.1 Primary search results

The Scopus database is used for research analysis. Table 1 shows the keywords and the corresponding number of documents used for the selection of perfect string. Total five strings are searched before finalizing the final string.

Table 1: Number of documents available related to keyword searched

String No	Keywords	No of Documents
1	ADDITIVE MANUFACTURING	31186
2	FAULT DETECTION	62927
3	3D PRINTING	38363
4	("3D PRINTER" AND "FAULT DETECTION" OR "MACHINE LEARNING" OR "REAL TIME MONITORING" OR "FUSED DEPOSITION MODELLING")	2929
5	("ADDITIVE MANUFACTURING" AND "FAULT DETECTION" OR "MACHINE LEARNING" OR "REAL-TIME MONITORING" OR "FUSED DEPOSITION MODELLING")	2509

Based on the above search results, one AND operator is used between master keyword and primary keyword, and OR operator is used to separate secondary keywords. Based on the above result final string is decided limited to English language and source type journal. For the study of the latest trends, search results are kept limited up to 2010. Table 2 shows the master keyword, primary keyword, secondary keywords, and final string limited.

Table 2: Table of the master, primary and secondary keywords

Master Keyword	"Additive Manufacturing"
Primary Keyword	"Fault Detection"
Secondary keywords	"Machine learning," "Real time Monitoring," "fused deposition modeling."
Final string limited to English language and source type as journal up to 2010	("ADDITIVE MANUFACTURING" AND "FAULT DETECTION" OR "MACHINE LEARNING" OR "REAL-TIME MONITORING" OR "FUSED DEPOSITION MODELLING")

2.2 Initial search results

For this survey, all types of documents are included from the source type journal. Search results are kept limited to the English language for better understanding of content, and for the study of recent trends, it is kept limited to the year 2021-2010. The total number of literature obtains are 1483. Table 3 shows the type of document and research article count related.

Table 3: quantitative analysis of document type

Type of Document	Publication Count
Article	1311
Review	108
Conference Paper	21
Note	4
Data Paper	3
Editorial	2
Retracted	1

2.3 Analysis of year-wise publication

Documents related to additive manufacturing were collected from the year 2010-2021. Table 4 shows the publication count pertaining to the year

Table 4: yearly trend in Additive Manufacturing

Year	Publication Count
2021	113
2020	437
2019	315
2018	250
2017	162
2016	84
2015	68
2014	28
2013	14
2012	8
2011	2
2010	2

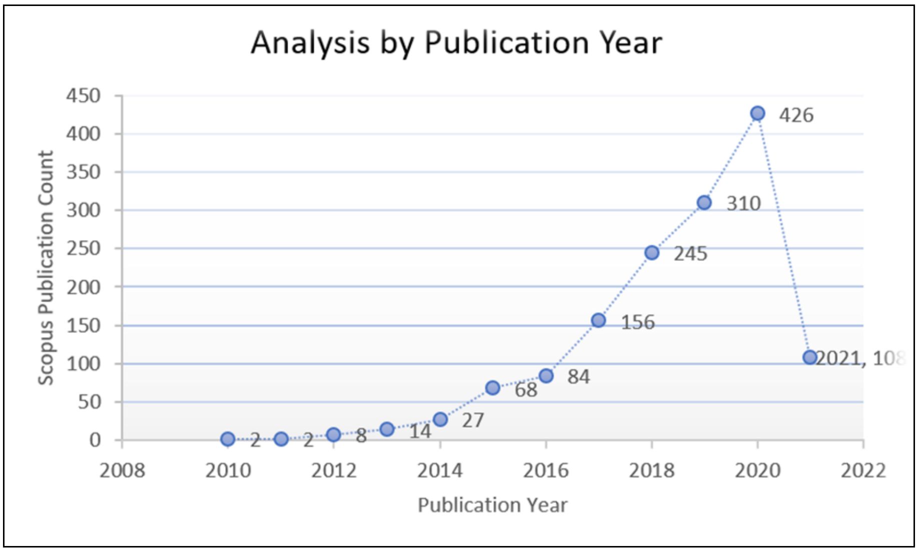

Fig 4: Yearly trend in Additive Manufacturing

Source: https://www.scopus.com/ (**assessed on 6th March 2021**)

From fig 4 and table 4, we can analyze that research in the field of additive manufacturing is increasing yearly except in 2021 as it is ongoing. From the above table, it is clear that additive manufacturing has become hot toping in the recent year considering its vast capabilities in various fields.

2.4 Geographical area wise analysis

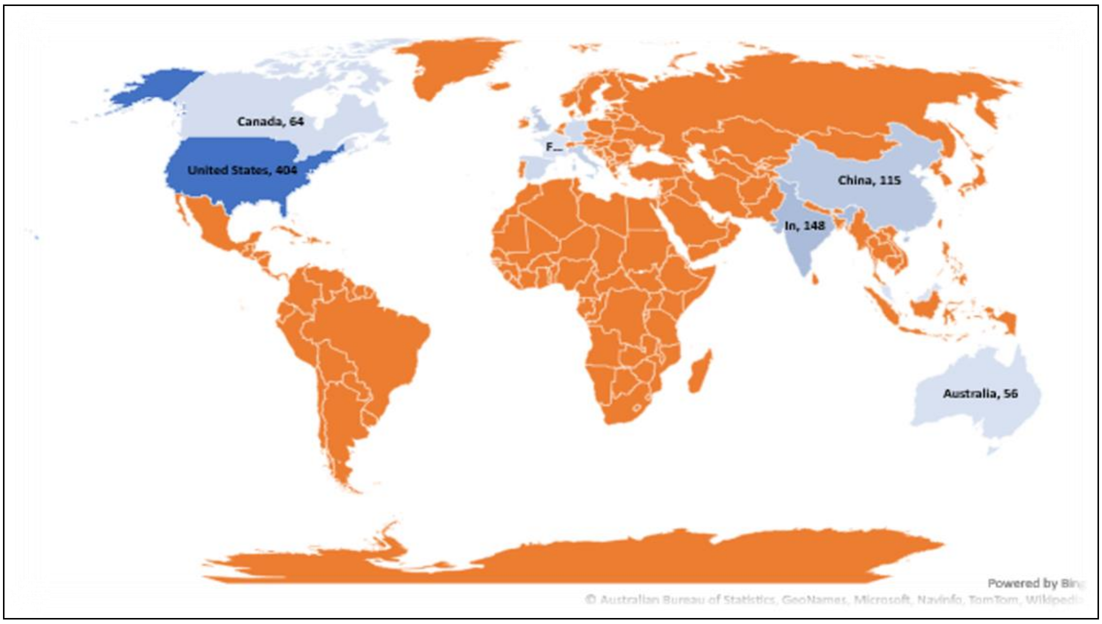

Fig 5: Publication Count by Geographical location

Source: https://www.scopus.com/ (**assessed on 6th March 2021**)

Fig 5 show count of publication by geographical area on the world map for better understanding. World map is used to better understand publication count corresponding to respective countries and comparative study respective to neighboring countries. From fig 5, we can see that maximum research is done in the United States (404), followed by India (148), China (115), Canada (64), Australia (56).

2.5 Analysis by subject area

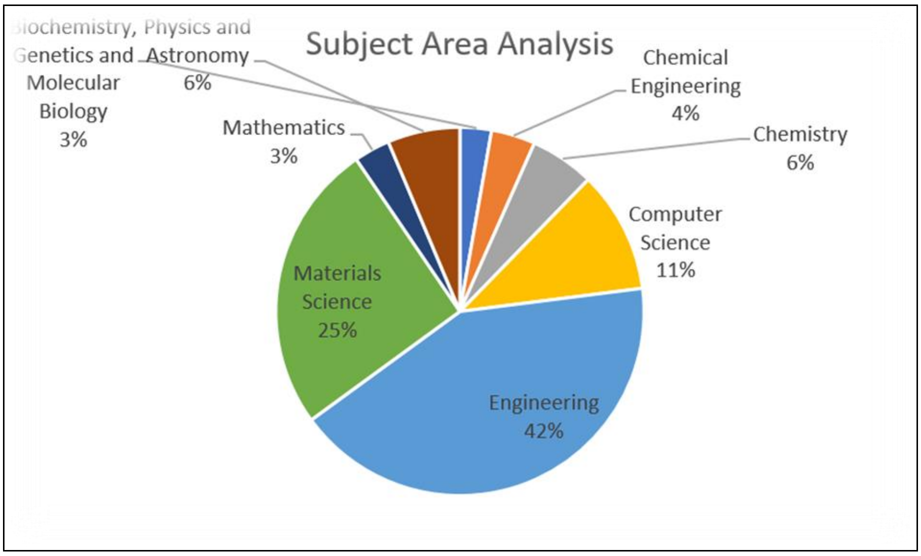

Fig 6: Subject area wise Analysis

Source: https://www.scopus.com/ (**assessed on 6th March 2021**)

Fig 6 shows subject area-wise classification for the additive manufacturing research area. Fig shows the top 8 subject areas in which the maximum research is carried out related to additive manufacturing. We can observe that in the field of engineering maximum of research is carried out that is (42%) followed by Material Science (25%), Computer science (11%), Chemistry and Astronomy each (6%) Biochemistry, Genetics and Molecular Biology, and mathematics each (3%)

2.6 Analysis based on Author

Fig 7 shows the number of articles published by each author. Fig shows the top ten authors based on document count. Singh, R has published the maximum number of documents that is 24. Other authors Basit A. W, Gaisford S, Goyanes A, Masood S. H, have published 14 documents each.

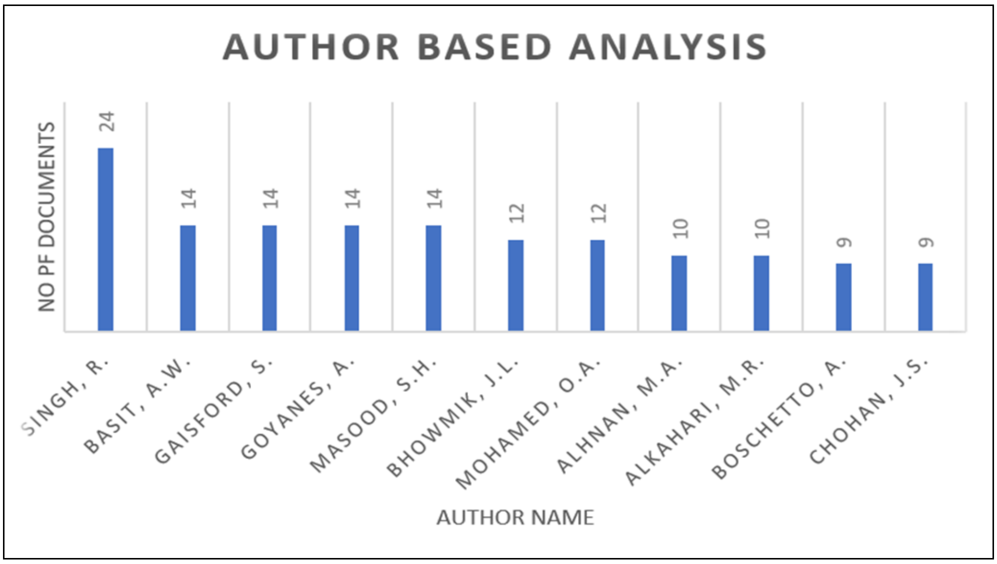

Fig 7: Statistical analysis based on authors

Source: https://www.scopus.com/ (**assessed on 6th March 2021**)

2.7 Affiliation based analysis

Fig 8 shows affiliation organization, institute, and the corresponding number of publications. The top 11 affiliated institutes, organizations, research centers are selected. Pennsylvania State University and Guru Nanak Dev Engineering College have published most 24 documents. University of Texas at El Paso, Georgia Institute of Technology, University Teknikal Malaysia Melaka, Nanyang Technology University has published more than 20 documents.

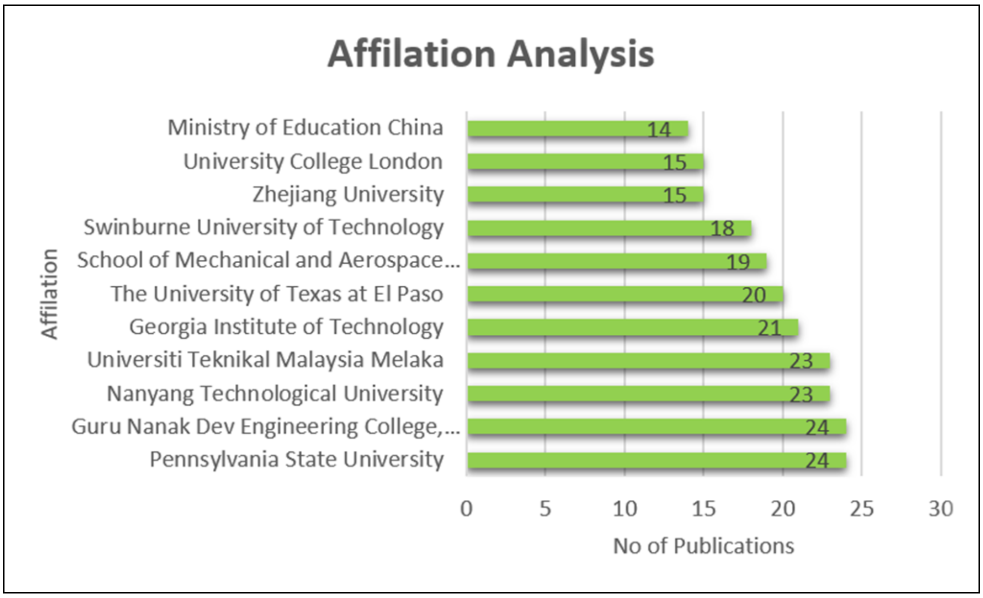

Fig 8: Statistical analysis based on affiliation

Source: https://www.scopus.com/ (**assessed on 6th March 2021**)

2.8 Statistical Analysis of Funding Sponsor

The top 10 funding sponsors are shown in fig 9. The maximum number of funding is done by National Science Foundation with 73 publications, followed by National Natural Science with 65 publications. U. S Department of Energy, Natural Science Engineering Research Council, European Regional Development Fund, Engineering, and Physical Science Research Council have published more than 24 documents.

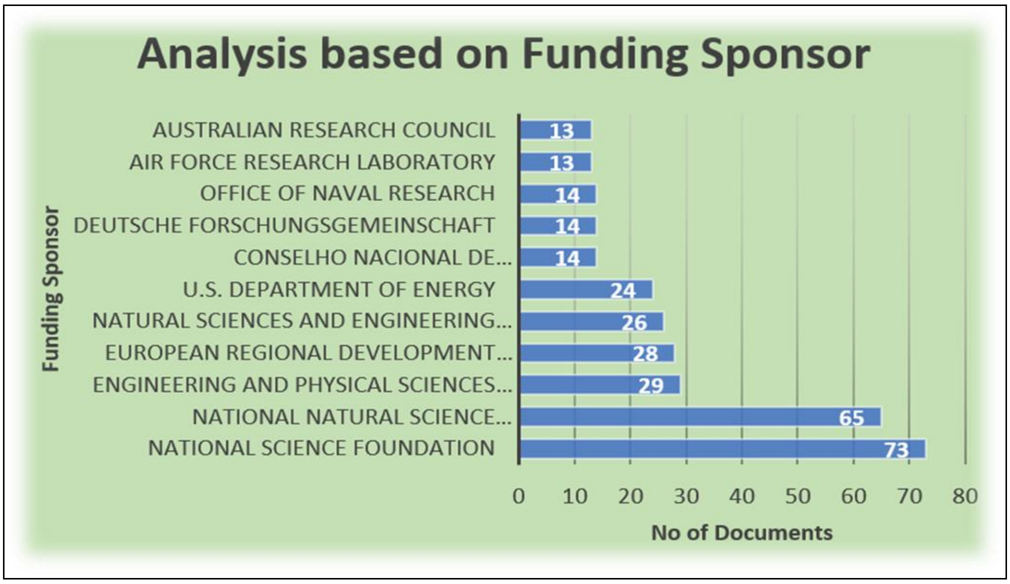

Fig 9: Analysis based on Funding Sponsor

Source: https://www.scopus.com/ (**assessed on 6th March 2021**)

2.9 Analysis based on source Title

Fig 10 shows the top 10 source title along with statistical data from the literature. It can be observed that Rapid Prototyping Journal has published whooping 111 numbers of documents, followed by Additive Manufacturing and International Journal of Advanced Manufacturing.

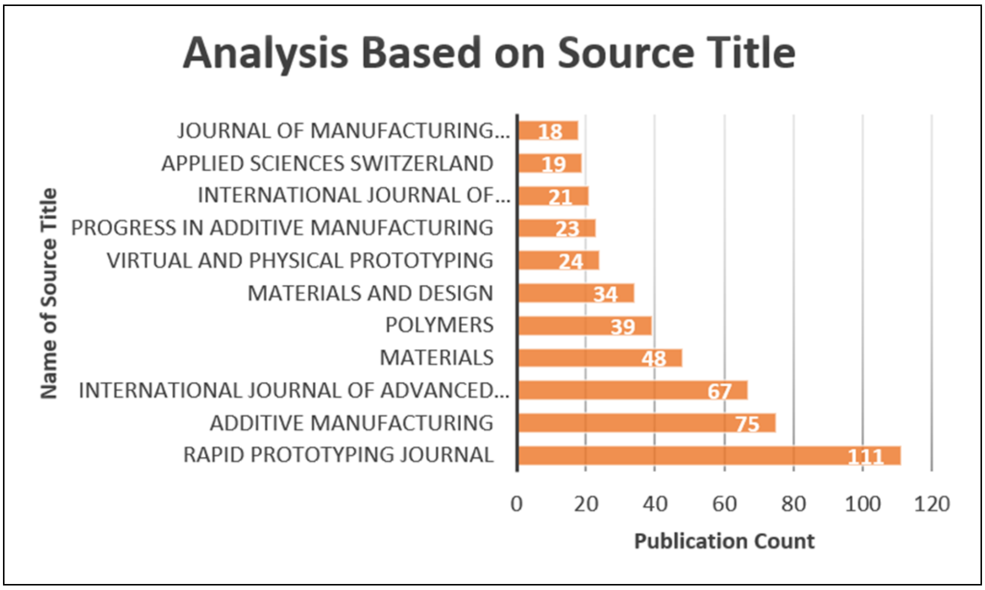

Fig 10: Statistical Analysis based on Source Title

Source: https://www.scopus.com/ (**assessed on 6th March 2021**)

2.10 Citation Analysis

Fig 11 shows the yearly citation count; we can observe that the citation count is increasing yearly. The maximum number of citations are done in the year 2020, which is 10751. It shows that research in AM area is increasing day by day.

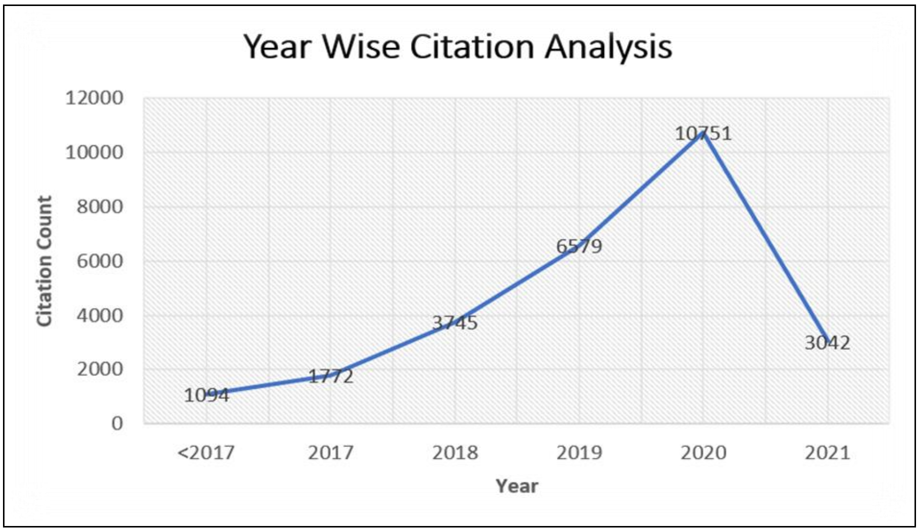

Fig 11: Statistical Analysis based on Citation Count

Source: https://www.scopus.com/ (**assessed on 6th March 2021**)

Table 5 shows the top 10 documents in the last five years that have maximum citation count. We can see that Additive manufacturing of carbon fiber reinforced thermoplastic composites using fused deposition modeling has the highest citation, which is 600.

Table 5: Analysis of Citation Count based on Publications

Sr No	Document Title	Authors	Journal Title	Yearly citation Count						
				<2017	2017	2018	2019	2020	2021	total
1	"Additive manufacturing of carbon fiber reinforced thermoplastic composites using fused deposition modelling."	Ning F., Cong W., Qiu J., Wei J., Wang S.	Composites Part B: Engineering	28	73	115	177	174	33	600
2	"A review of melt extrusion additive manufacturing processes: I. Process design and modelling."	Turner B.N., Strong R., Gold S.A.	Rapid Prototyping Journal	60	80	122	142	146	37	587

3	"Optimization of fused deposition modeling process parameters: a review of current research and future prospects"	Mohamed O.A., Masood S.H., Bhowmik J.L.	Advances in Manufacturing	16	44	68	117	129	38	412
4	"Additive manufacturing of PLA structures using fused deposition modelling: Effect of process parameters on mechanical properties and their optimal selection."	Chacon J.M. et al.	Materials and Design	0	2	52	119	156	33	362
5	"3D Printing multifunctionality: Structures with electronics."	Espalin D., Muse D.W., MacDonald E., Wicker R.B.	International Journal of Advanced Manufacturing Technology	65	54	59	72	70	11	331
6	"3D printing for the rapid prototyping of structural electronics."	MacDonald E. et al.	IEEE Access	61	49	62	56	70	17	315
7	"Material issues in additive manufacturing: A review."	Singh S., Ramakrishna S., Singh R.	Journal of Manufacturing Processes	0	10	50	86	112	24	282
8	"A review on additive manufacturing of polymer-fiber composites"	Parandoush P., Lin D.	Composite Structures	0	1	25	84	143	27	280
9	"A review of melt extrusion additive manufacturing processes: II.	Turner B.N., Gold S.A.	Rapid Prototyping Journal	23	27	47	79	85	19	280

	Materials, dimensional accuracy, and surface roughness."									
10	"Real-time monitoring of laser powder bed fusion process using high-speed X-ray imaging and diffraction."	Zhao C. et al.	Scientific Reports	0	3	31	74	90	23	221

2.11 Network Analysis

Network analysis is used to represent graphical relations between various parameters. In this survey, VOS viewer and GEPHI software are used for network analysis using the Scopus database. Network analysis is to form a relationship network between various computable parameters to better understand parameters and their linkage with other parameters.

2.11.1 Network Analysis of Keywords

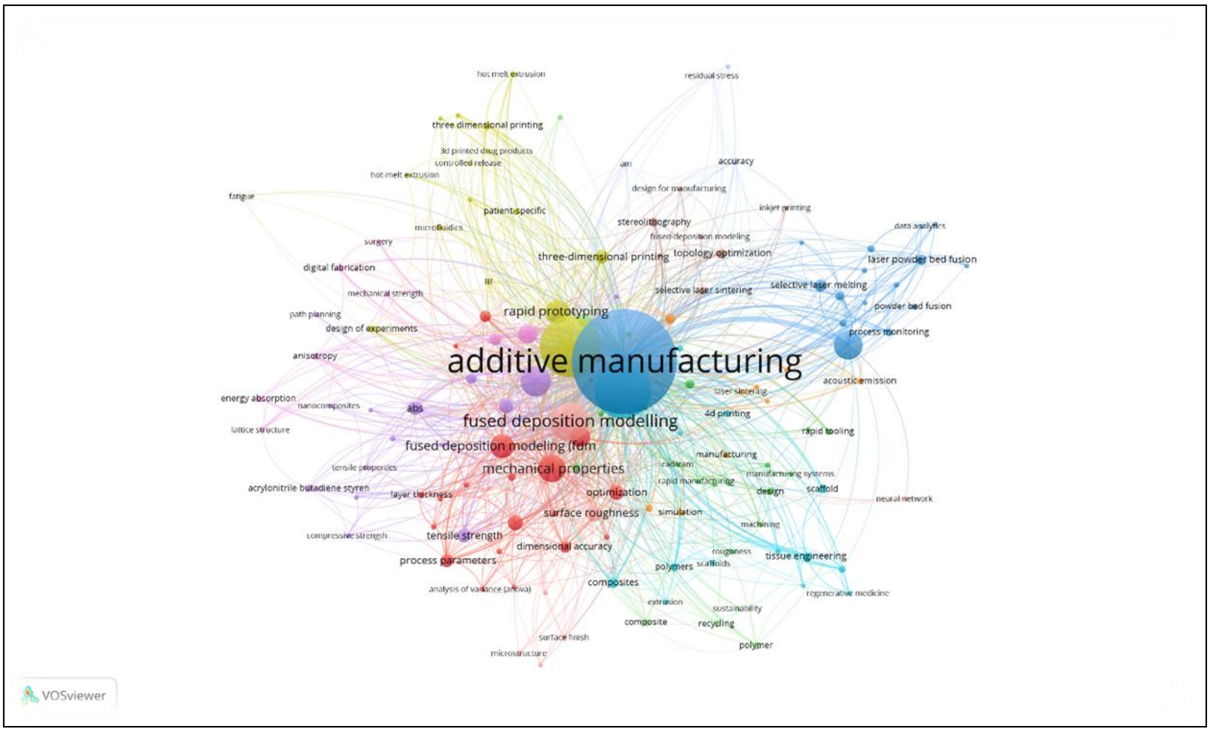

Fig 12: Network diagram based on Keywords

Source: (https://www.scopus.com/ and https://www.vosviewer.com) (**assessed on 6th March 2021**)

Fig 12 shows a network diagram using keywords. Each circle represents a keyword; the circle's size depends on the number of keyword occurrences. More the occurrence of keyword bigger the circle and vice versa. Distance between circles is dependent of the relation between keywords. If keywords are strongly related, then space is very less, as we can see for additive manufacturing and rapid prototyping. The minimum number of occurrence of keywords is kept to 5, for which total of 3481 keywords are selected from which 140 words meet the threshold.

2.11.2 Network Analysis of Author and Co-Authors based on Co-Appearance

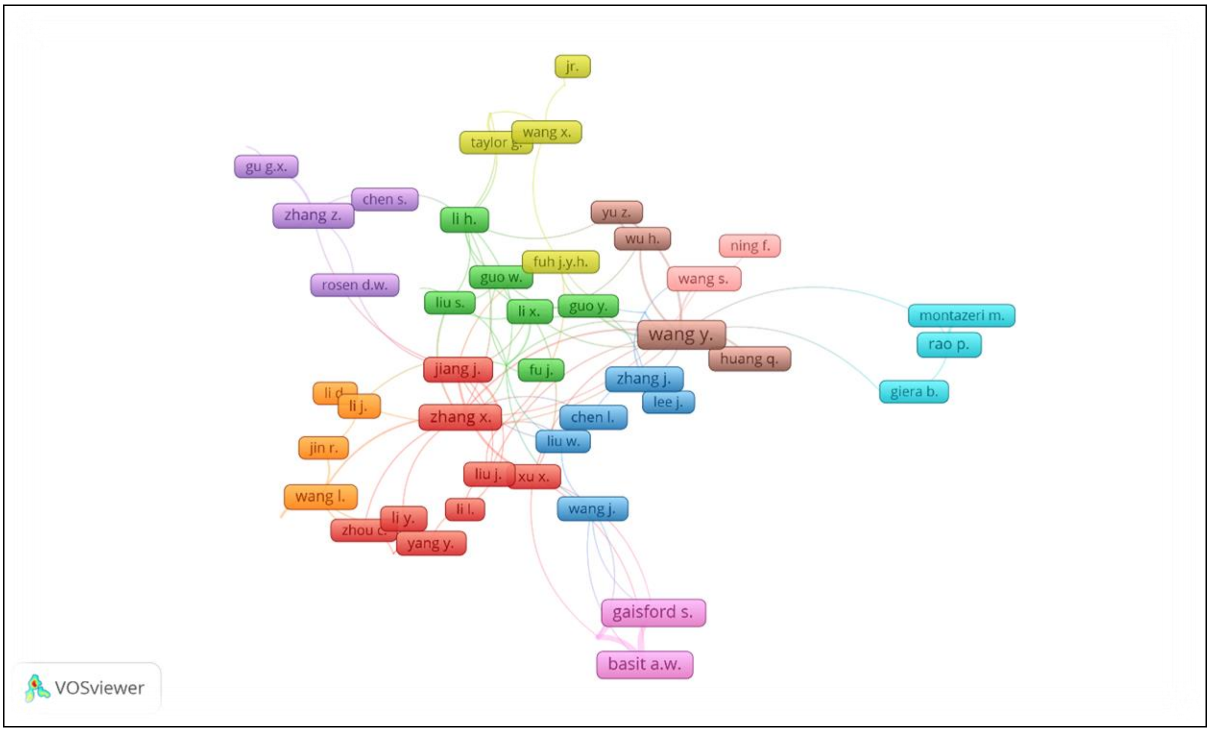

Fig 13: Author and Co-Author based Network Analysis

Source: (https://www.scopus.com/ and https://www.vosviewer.com) (**assessed on 6th March 2021**)

Fig 13 shows the network diagram of author and co-author based on co-appearance in the same paper. For this network diagram, the minimum number of documents by the author is selected to 4, and the minimum number of citations is kept as 0. A total of 10 clusters are formed, which contains 56 authors and co-authors connected by 108 links. This diagram helps to identify the collaborative work done by authors and co-authors. A link is used to show collaborative work between authors and co-authors.

2.11.3 Publication Map and citation cluster Network Analysis

Fig 14 shows the network analysis of the Publication Map and citation cluster created with GEPHI software. A node represents the publication title, and edges represent collaborative works between different authors. For this, the Fruchterman Reingold layout is used, which forms 3035 nodes and 2607 edges. A dark dot represents the higher number of citations received by the publication title.

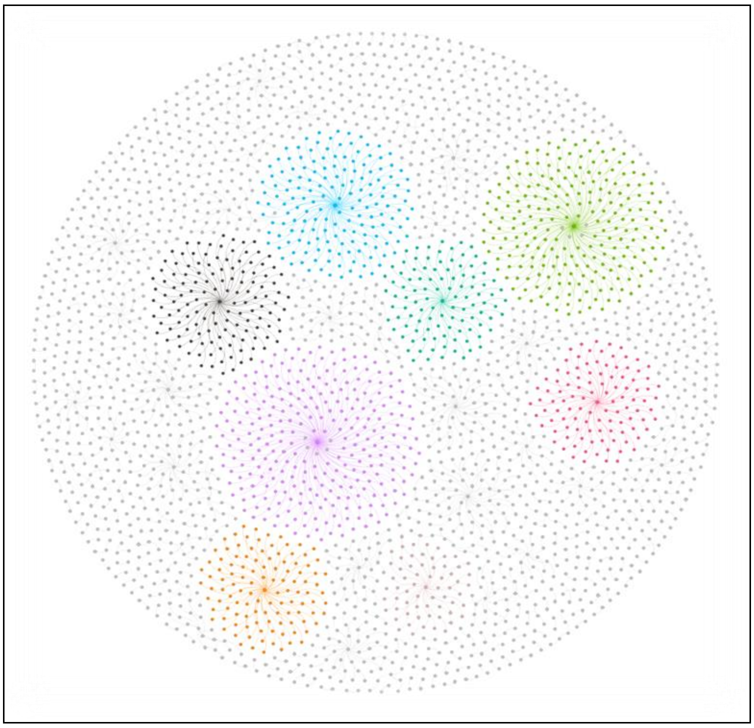

Fig 14: Publication Title and Citation Cluster-based Network Analysis

Source: (https://www.scopus.com/ and https://www.vosviewer.com) (**assessed on 6th March 2021**)

2.12 ProKnow-C Analysis -

Table 6 shows a bibliometric portfolio comprised of 10 articles. For this analysis, the Scopus database is used. Primarily by Keyword string total of 1483 results are obtained. These results are then filtered based on the availability of the full article then the search is reduced to 536 documents. Further study is filtered based on the alignment of document title with the topic and scientific recognition of topic, and then the search is reduced to 16 documents. Lastly, the study is further refined based on abstract alignment with topic and citation count, which results in 10 documents. Author Zhao C. has the highest 221 citations in reference of the bibliography portfolio, followed by Gordeev, E.G, Galushko A.S, Ananikov V.P. with 59 citations.

Table 6: Articles that comprises Bibliography portfolio

Sr No	Author	Article Title	Journal	Year	Citation
1	Scime L. et al.	"Layer-wise anomaly detection and classification for powder bed additive manufacturing processes: A machine-agnostic algorithm for real-time pixel-wise semantic segmentation."	Additive Manufacturing	2020	4
2	Baumgartl H. et al.	"A deep learning-based model for defect detection in laser-powder bed fusion using in-situ thermographic monitoring."	Progress in Additive Manufacturing	2020	22
3	Okaro I.A. et al.	"Automatic fault detection for laser powder-bed fusion using	Additive Manufacturing	2019	20

		semi-supervised machine learning."			
4	Wasmer K. et al.	"In Situ Quality Monitoring in AM Using Acoustic Emission: A Reinforcement Learning Approach"	Journal of Materials Engineering and Performance	2019	12
5	Lane B., Yeung H.	"Process monitoring dataset from the additive manufacturing metrology testbed (AMMT): Three-dimensional scan strategies."	Journal of Research of the National Institute of Standards and Technology	2019	7
6	Montazeri M. et al.	"In-process monitoring of material cross-contamination defects in laser powder bed fusion."	Journal of Manufacturing Science and Engineering, Transactions of the ASME	2018	23
7	Gordeev E.G. et al.	"Improvement of quality of 3D printed objects by elimination of microscopic structural defects in fused deposition modelling."	PLoS ONE	2018	59
8	Zhao C. et al.	"Real-time monitoring of laser powder bed fusion process using high-speed X-ray imaging and diffraction."	Scientific Reports	2017	221
9	Salary R. et al.	"Computational Fluid Dynamics Modeling and Online Monitoring of Aerosol Jet Printing Process"	Journal of Manufacturing Science and Engineering, Transactions of the ASME	2017	46
10	Qian B. et al.	"Monitoring of temperature profiles and surface morphologies during laser sintering of alumina ceramics."	Journal of Asian Ceramic Societies	2014	10

Fig 15 shows the number of articles in the bibliographic portfolio periodically. We can observe that all journal has one each article except Journal of Manufacturing Science and Engineering, Transactions of ASME, which has two articles.

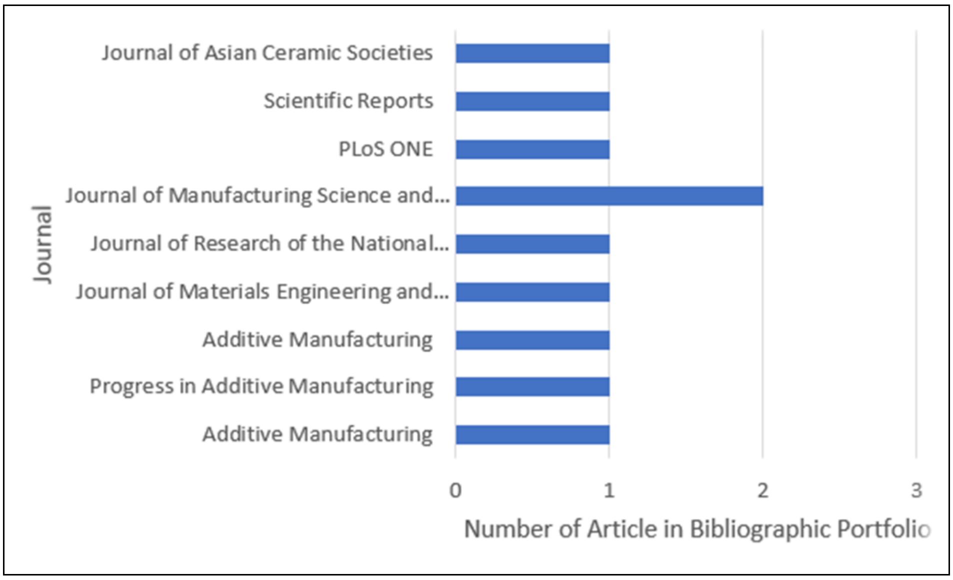

Fig 15: No. of Article in bibliographic portfolio by periodical

Table 7 shows the approach used in research articles. Article 2 and 8 propose a way to detect faults in laser powder-based fusion AM. Article 1, 3, and 4 propose fault localization techniques for different AM techniques. Article 5 studies database for different 3D scan strategies, and article 9 provides a Simulink approach for morphology trend study in aerosol jet printing.

Table 7: Approach used in articles in bibliometric portfolio

Sr No.	Articles	Approach used research
1	"Layer-wise anomaly detection and classification for powder bed additive manufacturing processes: A machine-agnostic algorithm for real-time pixel-wise semantic segmentation."	The research provides a way to implement real-time monitoring for powder bed AM for fault localization by pixel-wise localization in each layer using CNN. The study incorporates various algorithms that are implemented on 6 six different machines operating on three different technologies laser fusion, binder jetting, electron beam fusion, to present each algorithm's accuracy to be superior to that of the previous one.
2	"A deep learning-based model for defect detection in laser-powder bed fusion using in-situ thermographic monitoring."	This study explores various anomaly detection techniques that can be used in Laser powder-based fusion AM. For detection, different methods are proposed, like melt pool monitoring or off-axis infrared monitoring. This research tries to provide a model for fault detection for low cost using heat maps and infrared imaging.
3	"Automatic fault detection for laser powder-bed fusion using semi-supervised machine learning."	The research implemented fault detection using ML to build components in areas of healthcare and aerospace. It tries to provide a certified component to reduce the cost of part certification.
4	"In Situ Quality Monitoring in AM Using Acoustic Emission: A Reinforcement Learning Approach"	The research tried to monitor AM components using acoustic emission and reinforced learning for mass production of AM components with the same standards.
5	"Process monitoring dataset from the additive manufacturing metrology testbed (AMMT):	The research explores the dataset available on 3D scan strategies pertaining to AM components. The dataset includes situation monitoring and metadata.

	Three-dimensional scan strategies."	
6	"In-process monitoring of material cross-contamination defects in laser powder bed fusion."	The research is focused on the detection of the onset of material cross-contamination with the help of the spectral graph approach. The study tries to reduce defects that occur in AM due to cross-contamination of material.
7	"Improvement of quality of 3D printed objects by elimination of microscopic structural defects in fused deposition modelling."	The article tries to provide an approach to assess the quality of 3D printed objects in FDM based on printing parameters. The study concludes that feed rate, geometry, and structure define the quality of components in a 3D printer.
8	"Real-time monitoring of laser powder bed fusion process using high-speed X-ray imaging and diffraction."	Using high-speed synchrotron hard X-ray imaging and diffraction techniques, the researchers expect to gain a deeper understanding of LPBF dynamics and kinetics. It provides a significant phenomenon in LPBF with respect to scientific and technological aspects. The study tries to provide the effect of solidification rate by quantitative measurement.
9	"Computational Fluid Dynamics Modelling and Online Monitoring of Aerosol Jet Printing Process"	The article explores morphological trends with various attributes as functions of CGFR and SHGFR using CFD simulation. The study proposes an image-based line morphology quantifier for the detection of incipient process drifts.
10	"Monitoring of temperature profiles and surface morphologies during laser sintering of alumina ceramics."	The study explores the process of defect formation in the laser sintering process by image capturing. It tries to provide a capturing system for the area of the metal pool and surrounding area.

3. Limitation of study, Challenges, and Future Scope

3.1 Limitation of the study

This study is limited to the Scopus database. There are other databases available like Science Direct, Web of Science, etc. Search results obtained are kept to the English language since it is widely used worldwide and source type only as Journal. Only the last 11 years of papers are examined for recent research analysis. Additive Manufacturing has a wide range of application areas that is expanding day by day; the study revolves around the results obtained by primary and secondary keywords.

3.2 Challenges

Additive Manufacturing is subjected to various defects that in result creates faulty or partly faulty components. Real-time monitoring can provide a means for the identification of these defects in the earliest stage. It is challenging to monitor the process as current 3D printers lack in-built sensors, so the mounting of sensors to the perfect location is challenging since the sensor position affects its data collection capabilities.

3.3 Future Scope

Additive Manufacturing is growing day by day; the application range of printed components by additive manufacturing is vast. Anomaly detection using real-time data can help to improve the overall working and efficiency of 3D printing. As the world moves to smart manufacturing additive manufacturing needs to be developed accordingly to bridge the gap between current manufacturing and smart manufacturing.

4. Conclusion

This study represents the bibliometric analysis of fault detection in Additive Manufacturing. For this study, the Scopus database is used. This study includes an analysis of 1483 documents that help identify research done in various areas related to AM its applications. The United States has published the most number of documents in this area, followed by India and China. Singh R has published most numbers of documents. Most of the study done is related to mechanical followed by material science and computer science. The study also includes analysis based on affiliation, keywords, Funding sponsor, and Source Title. Network analysis is carried out for better understanding between Author co-authors, subject area, and keywords. Additive Manufacturing techniques need to be improved to match up to smart manufacturing so they can effectively use in industry 4.0

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