



REVIEW

# A Review on Machine Learning, Big Data Analytics, and Design for Additive Manufacturing for Aerospace Applications

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Submitted: 8 September 2021 / Revised: 22 May 2022 / Accepted: 13 June 2022 / Published online: 12 July 2022

Additive manufacturing (AM) has emerged as a promising technology to cater to the increasing demand for the fabrication of multi-functional, multi-material, and complex parts. AM is revolutionizing production and product development in the aerospace, automotive, and medical fields. However, mismatch in material properties, pervasive imperfections in the printed part, and lack of build consistency are crucial concerns. Higher accuracy in AM processes primarily depends on controlling various aspects of the process. In the last few years, machine learning, data analytics, and design for additive manufacturing have been the most extensively used techniques to address the vital concerns of additive manufacturing. Despite well-known techniques, very few studies reported applications of these techniques for aerospace. Specifically, this study comprehensively reviews recent advancements in the design for additive manufacturing (DfAM) and applications of machine learning and big data analytics to address the prime concerns of AM. The DfAM emphasizes issues and opportunities for topology optimization and methods for generative design for weight reduction and manufacturing of products with high resolution. Simulation and modeling techniques that are being used to improve geometric quality and process analysis are discussed to enable its potential for different applications. Further, automation of AM process using the Internet of things and knowledge-based systematic process planning is discussed to address key issues in process planning of multiple parts. Finally, the current challenges and scope for algorithmically driven AM processes are summarized with the trends of automation in AM to ensure greater efficiency and a better lifecycle of AM products in the era of industry 4.0.

**Keywords** additive manufacturing, aerospace, big data analytics, DfAM, IoT, machine learning

## Abbreviations

ACO	Ant-colony optimization
AI	Artificial intelligence
AHP	Analytical hierarchy process
AM	Additive manufacturing
ANN	Artificial neural networks
BAAM	Big area additive manufacturing
BDA	Big data analytics
BESO	Bi-directional evolutionary structural optimization
BD-SSAM	Big data-driven sustainable and smart additive manufacturing
BOL	Beginning of life
CAD	Computer aided design
CNN	Convolutional neural networks
DED	Directed energy deposition
DAE	Deep autoencoders
DBN	Deep belief networks
DBNN	Deep bayesian neural networks
DfAM	Design for additive manufacturing
DQINN	Deep quantum inspired neural network
DMLS	Direct metal laser sintering
DL	Deep learning
DNN	Deep neural network
EBM	Electron beam melting
GD	Generative design
GMAW	Gas metal arc welding
HASM	Hybrid additive-subtractive manufacturing

## 1. Introduction

Manufacturing processes are continuously evolving to develop innovative, sustainable, and complex products having stringent technical requirements. One such emerging technology is additive manufacturing. The concept of additive manufacturing of a product has existed for the past few decades. Additive manufacturing (AM) creates objects or products decrementally, layer by layer, with the aid of computer model data till a 3-dimensional object is manufactured. AM provides distinguished benefits for manufacturing customized

This invited article is part of a special issue in the *Journal of Materials Engineering and Performance* entitled “Space and Aerospace Exploration Revolution: Metal Additive Manufacturing.” The issue was organized by Shahrooz Nafisi, Relativity Space; Paul Gradl, NASA Marshall Space Flight Center; Douglas Hofmann, NASA Jet Propulsion Laboratory/California Institute of Technology; and Reza Ghomashchi, The University of Adelaide, Australia.

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HAZ	Heat-affected zone
IoT	Internet of things
K-NN	K-Nearest neighbor
LBAM	Laser-based additive manufacturing
LBM	Laser Beam Melting
LSTM	Long Short-Term Memory
ML	Machine Learning
MODBNE	Multi-Objective Deep Belief Networks Ensemble
MCDM	Multi-Criteria Decision-Making
OEMs	Original Equipment Manufacturers
PBF	Powder Bed Fusion
RCN	Recurrent Convolutional Networks
SDAE	Stacked Denoising Autoencoders
SLM	Selective Laser Melting
SSAM	Sustainable and Smart Additive Manufacturing
SVM	Support Vector Machine
WAAM	Wire Arc Additive Manufacturing

products compared to the traditional manufacturing processes. Also, it enables the production of components having complex geometries on macro, meso, and micro scales (Ref 1).

AM finds its application in major industries like the aerospace, automobile, and medical sectors. But it has predominant applications mostly for aerospace components about 18.2% of the global industry market share in 2017 (Ref 2-6). Some of the applications include manufacturing and rapid prototyping of aircraft engines, wing assemblies, high-value aerospace brackets, bracket for high lift device, and a central wing for the passenger-plane. AM also assists in reducing the number of individual parts in the component and hence lowers the cost. Topology-based complex component optimizations can be effectively realized by AM compared to conventional manufacturing processes. Studies also attempted to examine process planning issues in a network of AM systems that account for part-to-printer assignment involving multiple parts and printers with scheduling objectives. A group of researchers proposed a decision-support tool that integrates production and distribution planning in AM (Ref 7-9).

AM produces near net-shaped products with almost the buy-to-fly ratio close to one. AM processes are mainly categorized into material extrusion, sheet lamination, powder bed fusion (PBF), binder jetting, directed energy deposition (DED), material jetting, and photopolymerization. Among the different AM technologies, DED and PBF are the most used in the aerospace industry, being metal AM against photopolymerization, binder jetting, material jetting, material extrusion, and sheet lamination techniques (Ref 10). The nomenclatures and trade names associated with various commercial metal AM processes are as shown in Table 1.

Critical attributes of AM within the aircraft industry are shown in Fig. 1. By appropriately integrating critical attributes of AM with the aircraft industry some of the supply chain and inventory issues could be effectively resolved. Singamneni et al. (Ref 11) presented the state-of-the-art of the application of AM in the aircraft industry considering the main hurdles, and the future possibilities.

In recent years, it has been shown that high performance structures can be effectively designed by combining topological optimization with AM (Ref 12). Topology optimization and generative design (GD) are the most predominantly used

structural optimization tools during design for additive manufacturing (DfAM). GD facilitates comparative evaluation of a multitude of design outcomes of the aerospace parts such as blades, compressors, airfoils, etc., that involve complex manufacturing processes. Advanced generative design software's enabling engineers to optimize aerospace designs to benefit in specific from AM processes (Ref 13). A significant mass reduction of about 50-60% was achieved by innovatively designing the aerospace components using topological optimization and AM technologies (Ref 14).

AM generates massive amounts of data during manufacturing that need to be collected and analyzed for better AM performance through cost-reduction. The AM is a data-intensive process that offers profound research opportunities using various machine learning (ML) techniques. A group of researchers attempted studies by combining ML techniques with AM for improving product quality, detect and predict different defects and distortions in the manufactured part, optimize the process times and reduce the costs. Attempts have been also made to apply ML on topology optimizations, microstructural materials design, and additive manufacturing (Ref 15).

Big data analytics (BDA) in AM provides an ideal solution in dealing with the massive data obtained from these processes. Efficient handling of big data forms a basis for establishing different quality control tools and techniques for various AM processes. Big data also aids in-process monitoring, analysis, and enhanced decision making for various AM in the aerospace industry.

In the era of industry 4.0, a group of researchers attempted automation in AM of multiple components to reduce the lead time with the amalgamation of AM and the Internet of things (IoT). A systematic process planning and control is very crucial for better decision-making while dealing with multiple orders of different parts from different companies with varied production requirements. A group of researchers addressed challenges for process planning in AM and the roles of decision-making process. One of the critical process planning issues in AM is deciding part orientation for minimum dimensional inaccuracy (Ref 16-18). Figure 2 shows the difficulties in decision-making that may arise due to multi-part production.

Ample efforts have been made by the researchers for obtaining enhanced product design and material properties for additively manufactured (AMed) components using simulation and modeling. It helps in determining the process parameters for defect-free and distortion-free AMed components. Researchers have attempted repairing aircraft components that are susceptible to cracking and distortions due to variable thermal stresses, temperatures, and corrosion using AM and cladding techniques. Attempts are also being made on big area additive manufacturing (BAAM) for large-size aerospace components, such as aircraft wings in a single print run to help manufacturers in cost-effective and faster production. BAAM is slowly coming up as an economical and flexible solution for manufacturing large parts and components. Over the last decade, extensive research has been carried out in the BAAM for manufacturing large products (Ref 19).

From the literature review, the authors found that in recent years sufficient attempts have been made by the researchers on reviewing AM processes for aerospace applications. Figure 3 depicts a summary of published papers included in the present study on DfAM, AM technologies, AM applications and

**Table 1 Nomenclature of various commercial metal AM processes (Ref 10)**

AM category	Sub-category	Other commercially known names
Powder bed fusion (PBF)	Laser-PBF (L-PBF)	Direct metal laser sintering, selective laser melting, direct metal laser re-melting
Directed energy deposition (DED)	Electron beam-PBF (EB-PBF)	Electron beam melting
	Wire arc AM (WAAM)	Wire and arc AM
	Laser powder DED (LP-DED)	Direct laser deposition, laser cladding, 3D laser cladding, direct laser fabrication, direct metal deposition, laser engineered net shaping, laser material/melting deposition, laser rapid/solid forming, laser hard bending/facing
	Laser wire DED (LW-DED)	

challenges, ML for AM, big data, process monitoring, and IoT for AM. The numbers shown in square brackets are the references.

The authors observed that review papers published in the domain of DfAM and topology optimization mainly discussed issues related to design and redesign for direct and indirect AM production, topology optimization techniques, and integration of topology optimization and AM.

On the other hand, the review papers published in the domain of AM mainly discussed the applications, benefits, and opportunities of AM for the aerospace industry, the evolution of metal AM for the aerospace industry, the supply chain configurations of the aircraft industry, and current outstanding issues. A group of researchers attempted to write review papers on AM process monitoring, big data, and IoT. These review papers mainly discussed inspection methodologies compatible with AM processes, in-situ process monitoring, big data, and how big data methods can offer a better future for AM technology, AM technology with the IoT, cloud, and cybersecurity, smart manufacturing, and the requirement for Industry 4.0 technologies for AM processes.

In recent years, review papers attempted machine learning for AM. These papers describe ML applications for AM, such as parameter optimization and anomaly detection, a comparative evaluation of the performance of various ML algorithms. Further, these papers discussed ML applications for DfAM and AI-enabled AM product development. A group of researchers also reviewed important aspects of deep learning (DL), the types of DL techniques and networks, and the development of convolutional neural networks (CNNs) architectures together with their main features.

AM being emerged as a promising technology to cater to the increasing demand for the fabrication of multi-functional, multi-material, and complex parts assisting in increasing product reliability with the use of ML, IoT, BDA, and cloud computing technologies. From the literature review, it is seen that the researchers have most extensively used ML, BDA, and DfAM techniques to address the major concerns of AM. Despite that, very few studies reported combinedly on recent advancements in AM, considering applications ML, BDA, IoT, and, knowledge-based process planning, simulation and modeling techniques for aerospace applications. There is a need for a comprehensive review that would be helpful for the young researchers, students, and decision-makers to understand the recent advancements and future perspectives of AM.

This review paper presents recent advancements in the DfAM and applications of machine learning and BDA to address the major concerns of AM. The main objective of a review paper is to evaluate the existing work to identify ambiguity and contradictions in existing data and explore the research gaps in AM for aerospace applications. This paper reviewed the application of machine learning to AM design, process optimization, process planning, monitoring, and quality control. Further, a survey on BDA and IoT is presented to address the major concerns of AM. This review also provides recent advancements in the DfAM. The DfAM emphasizes issues and opportunities for topology optimization and methods for generative design for weight reduction and manufacturing of products with high resolution. This review helps researchers and students to have a good understanding of recent advancements in AM. The procedure followed for writing a review paper is shown in Fig. 4.

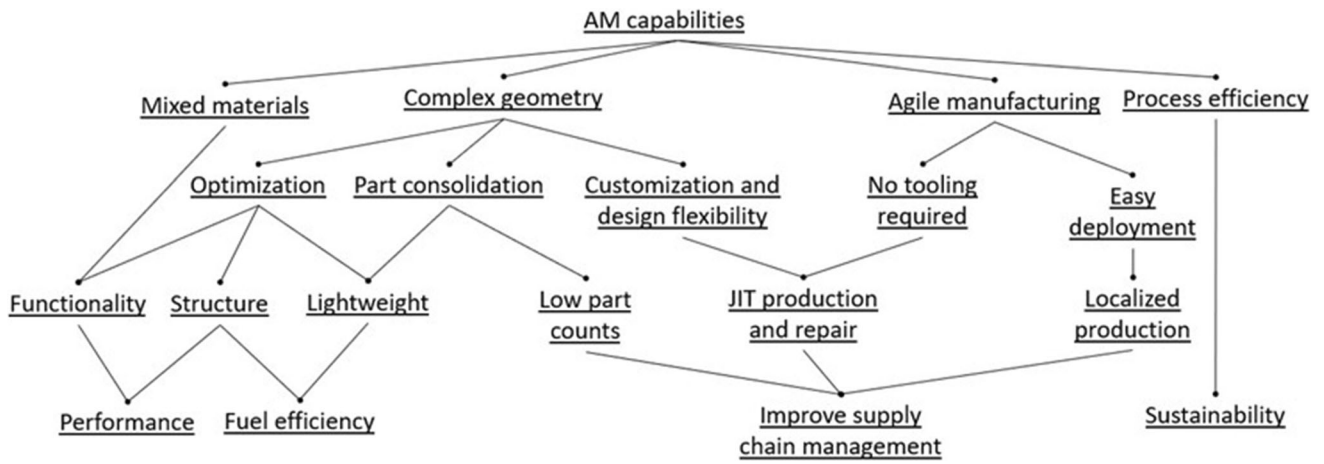


Fig. 1 Critical attributes of additive manufacturing (AM) within the aircraft industry (Ref 11)

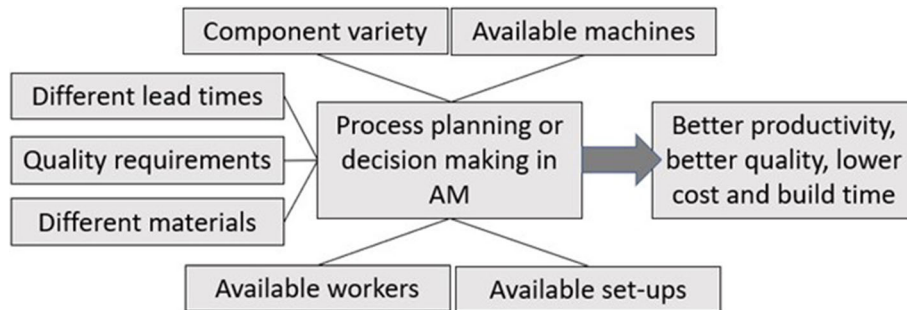


Fig. 2 Difficulties in decision-making for multi-part production (Ref 16)

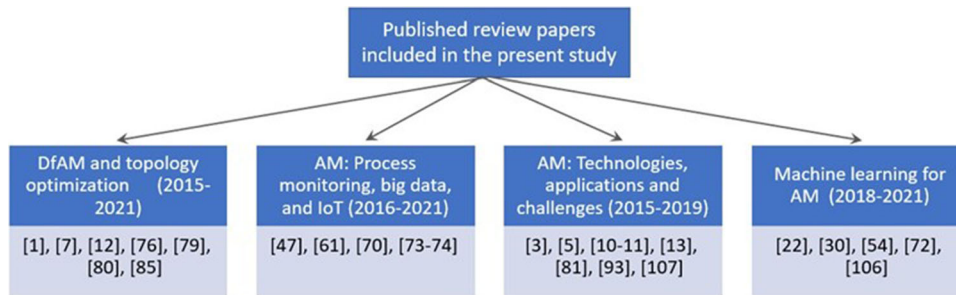


Fig. 3 A summary of published review papers included in the present study

Initially, the authors carried out a critical and constructive analysis of published literature referring to databases such as Scopus, Web of Science, IEEE Xplore, ScienceDirect, Research Gate, and The Directory of Open Access Journals. Literature reviews as integral parts of master theses and doctoral theses are not considered. A systematic quantitative literature review was conducted with a view to identifying the areas covered by existing research, and also revealing the gaps. A systematic literature review approach used in the present study for having new insights and different perspectives on the existing literature is shown in Fig. 5.

Keywords used for the literature searches were ‘Additive manufacturing’, ‘ML’, ‘DfAM’, ‘GD’, ‘Topology optimization’, ‘IoT’, ‘BAAM’, ‘BDA’, ‘Simulation and modeling’ and a combination of terms including ‘Recent advancements’, ‘AM’, ‘Aerospace’. The search was restricted to recent papers

published mostly in the last five years. Original research articles, review articles, conference proceedings articles, invited articles, magazine/press release articles, and book chapters relevant to the topic of the study were considered for the present review. For each collected paper, the author(s), year of publication, journal, and indexing with databases were noted. Each paper was categorized based on the classification themes considered for the present review such as ML techniques to address major concerns of AM, recent advancements in the DfAM, BAAM, BDA, IoT, simulation, and modeling for aerospace applications. The important key points are extracted from the papers, the necessity of these studies was understood, and the strength and weaknesses of these studies were identified. Finally, a problem statement was framed based on the research gaps identified through a systematic literature review.

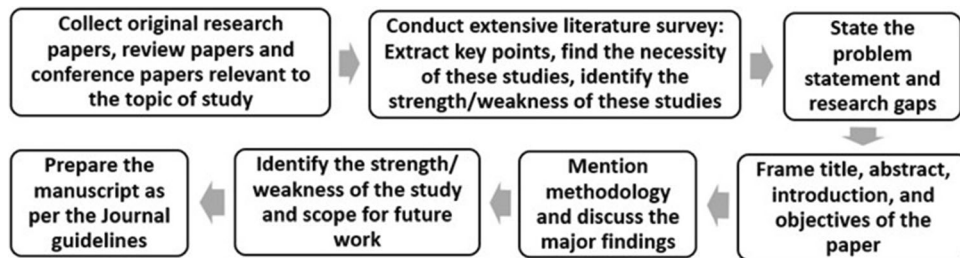


Fig. 4 Procedure to write a review paper

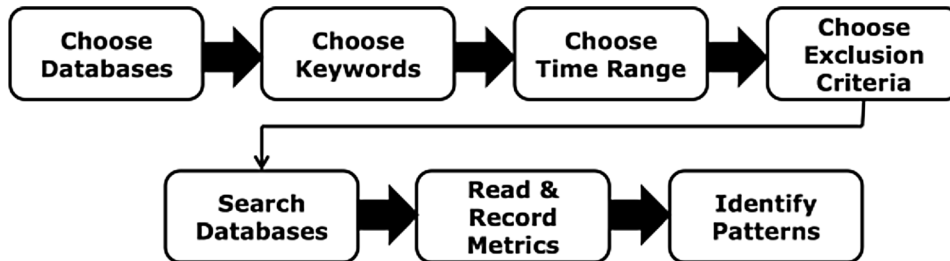


Fig. 5 A systematic literature review process (Ref 20)

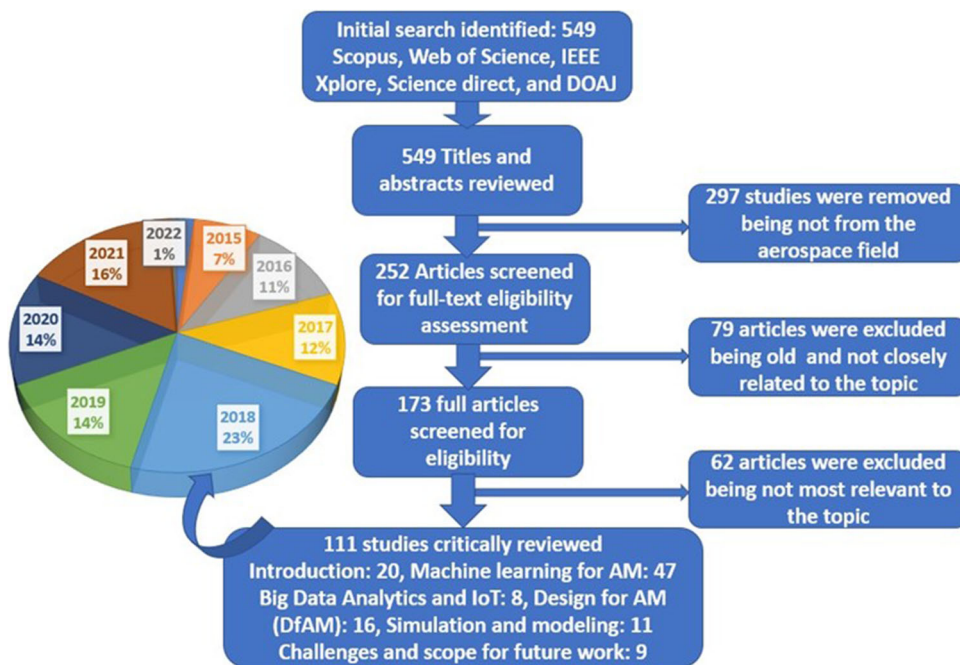


Fig. 6 Matrix showing paper searched, screened, and critically reviewed

Papers critically reviewed are about 21% of the total number of papers searched and 44% of the total papers screened for full-text eligibility assessment. The decision for a critical review of the paper was based on obtaining the most relevant, recently published work from peer-reviewed indexed journals and conference proceedings. Figure 5 depicts the article selection matrix starting from the initial search identified on recent advancements in AM to finally articles selected for full-text review for aerospace applications. However, titles and abstracts were reviewed for the recent relevant papers of the

study. Finally, the most relevant studies are included for the classification theme considered, as shown in Fig. 6.

The present work eventually lists challenges and scope for further research in the AM to implement these processes effectively for aerospace applications. A complete article is divided into different sections. Section one discusses the critical attributes of AM within the aircraft industry and outlines the importance of the present study. Section two discusses applications of machine learning for additive manufacturing. This section has four sub-sections: ML for part design, ML for

process optimization, ML for in-situ process planning and monitoring, and ML for quality control. Section three discusses applications of BDA and IoT for AM. Section four discusses the DfAM which has three sub-sections: Topology optimization, generative design, and modeling and simulation of AM processes. Topology optimization and generative design techniques are the most predominantly used structural optimization tools during DfAM. Recent advancements and applications of these techniques are discussed in section four. Then modeling and simulation of AM processes with the strength and weaknesses of studies are discussed. Finally, challenges, the scope for AM processes, and conclusions are presented.

## 2. Machine Learning for AM

The buzzwords Machine learning (ML) and deep learning (DL) often used interchangeably, and both fall under the broad category of artificial intelligence (AI). ML is a branch of AI that is concerned with the programming and training of programs to optimize a performance criterion using experience or example data (Ref 21). ML techniques are classified into supervised, unsupervised, semi-supervised, and reinforcement learning. However, DL which is an evolution of machine learning uses a programmable neural network that can learn and make

intelligent decisions on its own. DL techniques mostly used when tackling large and complex data.

Recent studies found the improvement in AM processes, design, and production with ML algorithms and techniques. ML is used in the AM process for metallic aerospace components to make them cheaper, faster, lightweight, and energy efficient. ML techniques also assist in decreasing the product development lifecycle of aerospace components by optimizing the AM process parameters for new alloys. The five main application domains for ML are semantic analysis, computer vision, natural language processing, prediction, and information retrieval. However, computer vision, information retrieval, and prediction are prominent application domains for AM. Figure 7 shows the taxonomy of different ML applications in the AM field.

In the cases where there is a known output, supervised learning algorithms fit hypotheses to training labeled datasets. For the unlabeled case, the trained algorithm is applied to it to predict the unknown case. In other words, for supervised learning, all the observations in the dataset are labeled, and the algorithms learn to predict the output from the input data. Also, the training set consists of many such input and output pairs. Supervised learning is classified into classification and regression. The classification problem involves qualitative labels, and the regression problem involves quantitative labels. In the cases where there is no known output, unsupervised learning is

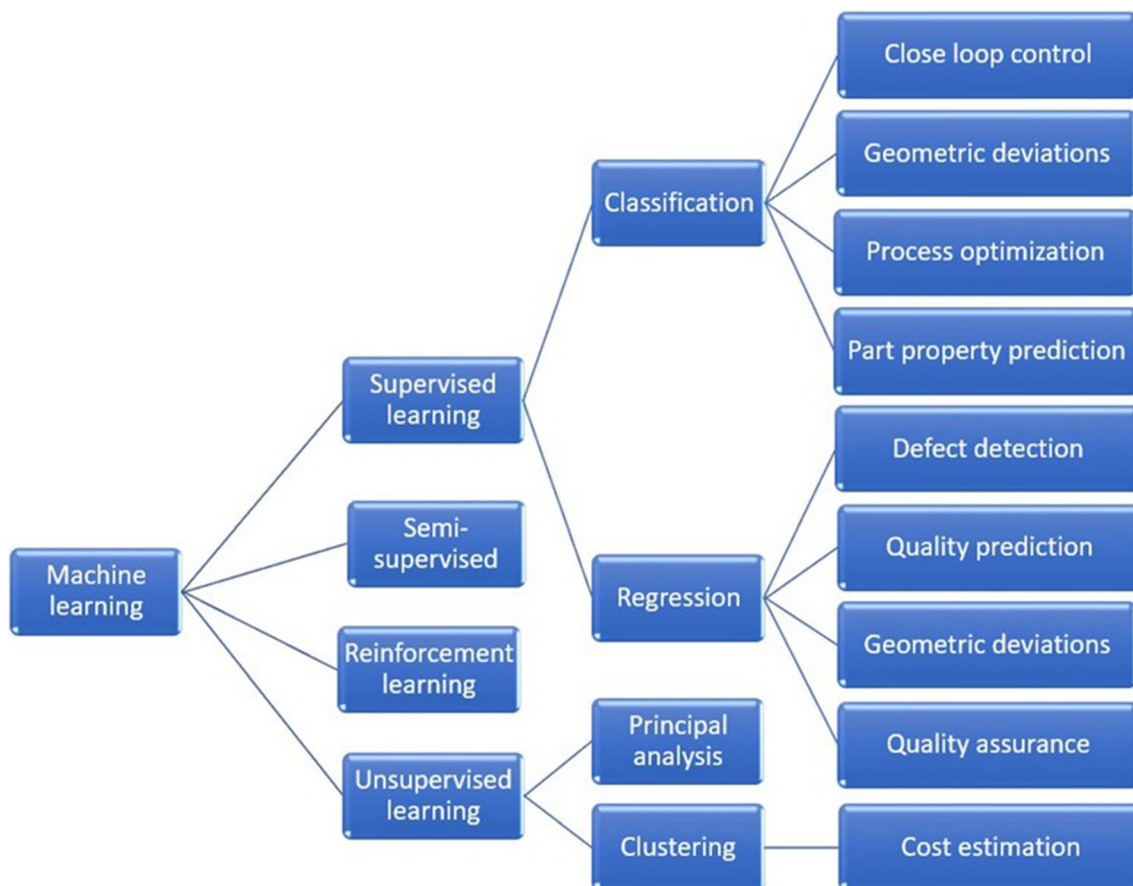


Fig. 7 Taxonomy of machine learning (ML) applications in the AM field (Ref 22)

implemented. In this case, the model will study the relationship among the input data. In other words, for unsupervised learning, all the observations in the dataset are unlabeled, and the algorithms learn to inherent structure from the input data. The two most common types of unsupervised learning for additive manufacturing are clustering and principal component analysis. In clustering, all the available data are clustered in groups based on their similarity.

In AM, the clustering technique is mostly used for cost estimation purposes. Reinforcement learning is used to map situations to actions to maximize a numerical reward signal (Ref 21). In reinforcement learning, the algorithms learn to react to an environment on their own. In this, the data is not predefined, and learning follows a trial-and-error method. The semi-supervised models use both labeled and unlabeled data for training. Attempts are being made to use ML techniques to reduce the cost and increase the speed of metal additive manufacturing for aerospace. Efforts are being taken to accelerate the product development lifecycle of aerospace components, while at the same time encouraging the production of lightweight, energy-efficient aircraft to support net-zero aviation targets.

Limited materials are available which satisfy the temperature and loading conditions for aerospace components. However, requirement of lighter, high-strength and higher temperature resistance material for better fuel efficiency narrowed down the availability of materials for the aerospace components. The availability of material further narrowed down considering the feasibility of material for AM. Continuing efforts are being taken by aerospace industries in designing new materials. However, it requires costly long testing and certification cycles. ML techniques are being increasingly used to rapidly develop cost-efficient laser powder bed fusion (L-PBF) process with optimized process parameters for new materials.

Recently, a few attempts have been seen to apply ML on topology optimizations, microstructural materials design and additive manufacturing. The deep learning model used for topology optimization improved the efficiency of the optimization process by formulating the problem as an image segmentation task. A deep learning approach is also used to accelerate 3D topology optimization and to determine the optimal computational strategy for its deployment. An AI-based deep generative design framework has been reported to generate numerous design options which are not only aesthetic but also optimized for engineering performance (Ref 15).

Attempts being also made using ML methods to speed up topology optimization problems. Structural optimization is generally used for designing airplane wings. However, the quality of design solutions depends on how the problem is parameterized. Hoyer et al. (Ref 23) proposed the implicit bias over functions induced by neural networks to improve the parameterization of structural optimization. Their work optimized the parameters of a neural network (reparameterization) which leads to different and often better solutions.

lattice-type structures which provide a combination of stiffness with light weight is being increasingly used in a variety of applications. However, design optimization of these structures must rely on approximations of the governing physics to render solution of a feasible mathematical model. Accurate analysis of lattice designs is a challenging problem due the need of high resolution. McBane and Choi (Ref 24) proposed a topology optimization formulation for lattice-type

structures that approximates the governing physics using component-wise reduced order modeling. Their proposed methodology reduced solution time by multiple orders of magnitude over a full-order finite element model with a relative error in the solution less than 1%. The offline training data set from such component-wise models is reusable, allowing its application to many design problems.

Ross et al. (Ref 25) used ML to perform a stiffness analysis on highly symmetric lattice geometries with periodic boundary conditions. Their approach approximates the material behavior of the vast space of all lattice geometries, which offers potential for real-time material feedback at the design stage. ML and DL applications in AM for design, process optimization, in-situ process monitoring and controlling, and quality control techniques are discussed in the following sections.

## 2.1 AM Design and Process Optimization

Machine learning techniques are being used to assist in decision-making while AM design, tolerancing assessment, and material selection for the aerospace industry. Attempts were made by the researchers to predict the build time for AM process using artificial neural networks (ANNs) considering the process parameters such as part volume, bounding-box volume, and Z-height. Chowdhury et al. (Ref 26) developed a geometry compensation method by predicting the surface quality of the fabricated part using a backpropagation neural network (BNN). The trained network modified the STL file whenever the CAD surface data for the new part showed or predicted poor surface quality.

Gu et al. (Ref 27) generated metamaterial structures of desirable toughness and strength using recurrent neural networks (RNNs). Some researchers have leveraged to implement neural networks (NNs) to generate lattice structures based on mechanical properties. As the design features in AM are gaining popularity and rapidly growing, various tools have been implemented using ML techniques to aid the designers. Yao et al. (Ref 28) designed and developed a hybrid tool using the ML technique to recommend the inexperienced designers about the design features. The tool was found very effective as it enabled the designers to explore the various AM design freedoms. The support vector machine (SVM) algorithm was used to target the features based on the designer's coding similarity to the part. In addition to the above applications, researchers have also implemented ML in AM for developing cost estimation frameworks. Based on the historical data, Chan et al. (Ref 29) developed a cost estimation model to predict the cost of a new printed job. They extracted prominent features from the design by using the similarities in the geometrical features and printing process parameters.

Process parameter optimization is usually a time-consuming and costly process. Manually handling data is a tedious process, and optimizing it becomes very time-consuming due to large samples in the data. Hence ML tools and techniques are utilized for the AM processes to optimize crucial main parameters for quality predictions or a set of other predictions (Ref 30). Researchers optimized process parameters for DED, L-PBF, material extrusion, and binder jetting AM processes. The studies usually focused on mapping complex relationships among material structure, properties, process parameters, and performance.

Sufficient efforts were made to monitor responses in the DED process with the BNN model by mapping the deposition

height with the process parameters such as feed rate, laser power, and scanning speed. There is a bulk of literature available that focuses on parametric optimization for DED processes. The major research focuses on controlling the resulting tracks and melt pool, which includes metal pool geometry (Ref 31), track width and height (Ref 32), and the thermal results of the pool (Ref 33). For L-PBF processes, the most important quality indicator was porosity, with many studies implementing ML algorithms to optimize the process parameters. (Ref 34-38).

Fathi et al. (Ref 39) implemented a bio-inspired optimization algorithm known as the Mutable Smart Bee algorithm for L-PBF. Their main aim was to develop a data-driven framework for optimizing the process parameters. Yang et al. (Ref 40) successfully predicted the melt pool width for different processing conditions using the Gaussian process regression ML technique.

Attempts were also made to predict and optimize the wear strength of the fused deposition modeling (FDM) parts using genetic algorithms and neural networks. It can be seen that ML is a powerful technique to predict and optimize the performance of AMed parts considering the effect of the process parameters. ML techniques made it possible to simulate different operating scenarios and adjust the control parameters for better machining performance. However, this study observes further scope for the use of advanced and hybrid optimization techniques to effectively monitor the AM process.

## 2.2 In-Situ Process Planning and Monitoring

Effective knowledge-based process planning does not ensure timely delivery of parts with minimum inventory and material waste. The scheduling and sequence planning with proper selection of production-relevant variables are crucial in AM due to the longer print times and flexible use of the production area. The selection of the process parameters that determine the performance of the fabricated parts in terms of their microstructure, dimensional and geometrical accuracies largely depend on the domain expert knowledge. However, reliable, and automated production process planning systems to capture, store, and reuse knowledge decision-making are needed.

The increasing use of AM processes in the industry requires an efficient system for having run-time availability of information to the ongoing manufacturing status. It creates challenges for production control for having short reaction times due to deviations in the manufacturing process. By having a suitable automatic identification and data capture system, a production system can be made capable of responding in real-time to unforeseen events. Ziegler et al. (Ref 41) discussed an approach for a production control system for a manufacturing line that considers characteristics of metal-based AM industries. Their study finds scope for further investigations considering the variance of possible AM-specific quality defects and their handling with a monetary evaluation.

Removing the support structures, especially for metal parts after the desired model is built is costly and time-consuming. Researchers also attempted to build support-less structures with a five-axis deposition machine. However, machine capabilities are to be utilized to the maximum extent with automated process planning. Xiao et al. (Ref 42) presented an automated method that allowed reorientation of the part while getting built without the use of supports using a five-axis machine. The proposed method required decomposition of the part into sub

volumes, and each sub volume with a given build direction was built with planar layers without support structures. Their study developed a process plan for manufacturing using algorithms to determine the sub-volumes, their orientations, and sequence. Finally, the viability of the proposed decomposition strategy and the effectiveness of the algorithms were validated with some practical examples. Their study pointed out that further research is needed in the domain of decomposition and slicing strategies for 5-axis hybrid manufacturing with uniform and non-uniform layer thicknesses. There is substantial potential in hybrid manufacturing technologies to explore in the future.

Chen et al. (Ref 43) presented a new process planning approach for a hybrid additive-subtractive manufacturing (HASM) system. The proposed method brings the AM and rapid machining technologies closer to direct digital manufacturing. The final design shape is obtained using an alternating sequence of AM and machining operations that alternately build and machine an in-process workpiece. Their study developed algorithms to find an optimal setup for both additive and subtractive manufacturing. The authors pointed out that further investigations are required to select the most economical build plate considering manufacturing and inventory constraints. Further, this work finds the scope for fixture design and AM orientations for multi-axis machining. There is also a need to investigate the effect of the process temperature changes and residual stresses that accumulate/release while alternating between AM and SM on dimensional and geometrical accuracy of finished parts.

In HASM, the most critical constraint is to prevent the collision between the in-process workpiece, the cutting tool, and the material-dispensing nozzle. It affects the determination of the alternating sequence. In another study, Chen et al. (Ref 44) presented a deterministic algorithm for automatically generating a collision-free sequence of hybrid manufacturing with the least alternations for a solid part. Ample computer simulation tests of the proposed algorithm confirmed the correctness and effectiveness of the proposed algorithm. Rossi et al. (Ref 45) optimized process planning and scheduling for hybrid additive/subtractive operations. However, further work is needed to obtain alternative solutions and objective quantitative evaluation based on cost, quality, and time criteria. Baumung et al. (Ref 46) presented an optimization model for the planning of AM systems using nesting algorithms for time-oriented workspace utilization. Their study finds scope for further research on accurate planning to ensure the calculated print time corresponds to the real one. It is also suggested to have studies considering the availability of the material stock on the AM machines in the optimization model and use it for selecting the operator slot.

In-situ monitoring and control technologies are rapidly growing, and it's one of the most focused areas concerned with applications of ML in AM. Various devices such as thermocouples, high-speed optical cameras, pyrometers, and other sensors are used in this technology (Ref 47). These monitoring and process control techniques with ML techniques are employed to detect and predict the part defects in AM processes. Imani et al. (Ref 48) used various ML techniques such as SVM, K-nearest neighbor (K-NN), and feed-forward neural networks (FNN) to collect and use data from real-time sensors with the primary objective of identifying or detecting the porosity for parts produced through L-PBF. Li et al. (Ref 49) determined dimensional deviation using an in-situ optical monitoring technique. In recent times, new technology of

acoustic monitoring is used to monitor print build. Shevchik et al. (Ref 50) used a CNN with acoustic emissions to detect defects in L-PBF due to lack of fusion. Attempts were made to determine overfill and underfill for the FDM process with an online closed-loop controller (Ref 51). Yao et al. (Ref 52) performed multifractal analysis for process control. Their study developed a closed-looped optimal control system to estimate the defect conditions in each layer. Further, the results obtained were used to predict the future evolution of defects in the layers.

A group of researchers used DL techniques for effective management of aircraft repair and maintenance. DL architectures, namely, deep autoencoders (DAE), long short-term memory (LSTM), CNNs, deep belief networks (DBN), and some of their hybrid forms are mostly used for diagnosis, anomaly detection and prognosis in parts of the aircraft. It was observed that DL models often outperformed model-based and statistical ML techniques.

Tian et al. (Ref 53) presented a DL-based data fusion method to predict porosity in laser-based additive manufacturing (LBAM) parts by leveraging the measured melt pool thermal history and two newly created deep learning neural networks. Their study developed convolutional neural networks to correlate in-process pyrometry images with layer-wise porosity and long-term recurrent convolutional networks (RCN) to correlate sequential thermal images from an infrared camera with layer-wise porosity. Layer-wise porosity was predicted combining the predicted results from CNN and RCN. Their study demonstrated the applicability of the DL-based data fusion method for in situ porosity detection in LBAM with high accuracy and relatively high efficiency.

Rengasamy et al. (Ref 54) reviewed deep learning architectures and their application in aircraft maintenance, repair, and overhaul (MRO). Their study finds the need for the creation of a repository of benchmark big data sets for aircraft maintenance, repair, and overhaul to assist researchers working in the similar domain. Gao et al. (Ref 55) performed fault diagnosis of aircraft's fuel system by combining deep belief networks (DBN) and deep quantum inspired neural network (DQINN) techniques. Their study observed the lowest standard deviation with DQINN compared to deep quantum network (DQN), DBN and BNN. ElSaid et al. (Ref 56) predicted excess vibration in aeroengine using combining LSTM and ant colony optimization techniques (ACO). Their study observed better results by optimizing LSTM via ACO.

Attempts also made in obtaining fault diagnosis and estimating remaining useful life of aeroengine using CNN, LSTM, hybrid stacked denoising autoencoders (SDAE) and SVM, DBN, and multi-objective deep belief network ensemble (MODBNE) (Ref 57-60). From the studies available, it can be seen that ML has been widely applied across a range of AM processes for the implementation of real-time process control. However, processing large amounts of input data in real time can require significant computational power. Therefore, more work is needed to successfully deploy ML algorithms for real-time applications with minimum requirement of computational power. Also, there is an immediate attention required in identification of causal relationships for a large volume of coincidental correlations resulting due to complexity of process factors and responses in a PBF (Ref 61). It has been observed that few studies attempted using DL techniques in AM. And, almost no attempt found on AM process monitoring using deep

Bayesian neural networks (DBNN) and hybridizations with fuzzy logic for aerospace applications.

This review finds scope for further investigations on a production control system for a manufacturing line considering the variance of possible AM-specific quality defects and their handling with a monetary evaluation. Also, studies have shown to explore the further substantial potential in hybrid manufacturing technologies. This review on knowledge-based process planning pointed out further research in the domain of decomposition and slicing strategies for 5-axis hybrid manufacturing with uniform and non-uniform layer thicknesses. There is ample scope available to explore the applications of data mining and ML techniques for process planning based on existing knowledge from fabricating parts. Also, further work is needed to obtain alternative solutions and objective quantitative evaluation based on cost, quality, and time criteria for integrated process planning and scheduling system. It is also suggested to have further studies on accurate planning to ensure the calculated print time corresponds to the real one and for selecting the operator slot based on the availability of the material stock on the AM machines.

### 2.3 Quality Control

Additively manufactured (AMed) parts, especially aerospace components, have complex geometries and require uniform material properties. However, AMed parts are susceptible to a lack of homogeneous material properties. ML techniques are used for inspection and validation purposes in AM. The focus is on surface structure and metrology, and defect detection. Senin et al. (Ref 62) developed a surface metrology advanced measurement technique combining ML and multi-sensor data. A group of researchers used various ML techniques, such as sparse representation, K-NN, NN, Naive Bayes, SVM, and decision trees, to classify dimensional variation in parts produced by the FDM process (Ref 63). Liu et al. (Ref 64) applied augmented layer-wise spatiotemporal log gaussian cox process (ALS-LGCP) model to binder jetted parts to quantify the porosity or spatial distribution of pores within each layer of the part. They also applied Bayesian predictive analytics to predict porosity zone areas in successive layers, with fidelity approaching 85%.

The undesirable process changes in the L-PBF process that brings inconsistency in part quality can be monitored by assessing the dimension of melt pools, which depends on the energy input and the cooling conditions. Schmid et al. (Ref 65) presented a new approach for the automated visual measuring of melt pools in cross-sections of parts manufactured by L-PBF. The melt pools were first segmented in the images with deep learning and are then measured. The proposed approach facilitated the measurement of the melt pools over the whole cross-section of the specimen and the evaluation of remelted melt pools, which were only partly visible. The proposed automated approach assisted in estimating trends over the build direction in a specimen and deviations in the energy input via the measured melt pool dimensions.

Parts fabricated using laser-based additive manufacturing (LBAM) lack in geometric accuracy needed for end-use applications due to uncertain distortions. Francis et al. (Ref 66) developed a novel deep learning approach that accurately predicts distortion well within LBAM tolerance limits by considering the local heat transfer for pointwise distortion prediction. The developed CAMP-BD (convolutional and

artificial neural network for additive manufacturing prediction using big data) computational framework contains a CNN for analyzing the thermal images and an ANN for including relevant process/design parameters. The output of the CNN and the output of the ANN are joined within CAMP-BD, through concatenation, and then further trained to give a final pointwise distortion prediction. The proposed deep learning model incorporates thermal information as well as process/design parameters for pointwise prediction of a variety of quality measures and is applicable for a wide range of part geometries.

In aerospace, wire arc additive manufacturing (WAAM) is used to produce large structures such as wing ribs and stiffened panels. WAAM deposits metal layer upon layer to manufacture 3D parts based on welding processes. It is mostly used in aerospace, marine, and automotive industries being cheaper and having higher material deposition rates reaching 50-130 g/min against 2-10 g/min in laser-based deposition methods. Researchers considered layer roughness, weld bead width, height, and penetration as the performance characteristic in WAAM. Layer roughness prominently affects the machining cost, mechanical properties of fabricated parts, and bonding between adjacent layers. Researchers also investigated the effect of straight paths and weaving path for material deposition on layer roughness in WAAM.

ML methods such as random forest and multilayer perceptron (MLP) which is also known as ANN are successfully implemented to accurately model surface roughness in WAAM using a weaving path. Both the methods effectively predicted the layer roughness for a given set of WAAM parameters, but random forest gave better results than MLP in terms of accuracy and computational time (Ref 67). In recent years, ML has gained increasing applications in a variety of AM domains due to its prominent performance in data classification, regression, and clustering. ML techniques can be successfully used in the DfAM to obtain optimized topological designs. DL architectures such as DAE, LSTM, CNNs, DBN, and some of their hybrid forms are found better for effective management of aircraft repair and maintenance. DL models often outperformed model-based and statistical ML techniques. ML algorithms are finding increasing applications in optimizing process parameters of AM processes.

ML and DL techniques find applications in DfAM (pre-manufacturing planning), process optimization, in-process defect monitoring and controlling, and quality control techniques. However, this study finds scope for AM process monitoring while manufacturing aerospace components using deep Bayesian neural networks (DBNN) and hybridizations with fuzzy logic. The next section discusses recent advancements in the DfAM to address the major concerns of AM. The DfAM emphasizes issues and opportunities for Topology optimization and methods for Generative Design for weight reduction and manufacturing of products with high resolution.

### 3. Big Data Analytics and IoT for AM

Big data analytics (BDA) with the Internet of things (IoT) assist in making quick decisions on the real-time analysis of substantial data that are collected using different sensors on AM systems. Big data are a collection of diverse massive structured, semi-structured, quasi-structured, and unstructured data sets collected from different sources that uses advanced analytic

techniques against traditional database and software techniques. Descriptive analytics provides effective visualization of the current AM process and business. Diagnostic analytics identifies the causes of problems in AM. Predictive analytics uses historical data and algorithms to predict AM process performance and future business needs. Prescriptive analytics recommends actions and strategies for AM process improvement and cost reduction using advanced analytical tools (Ref 68). Figure 8 shows the ways that BDA can be used for AM to enhance the quality of its products.

Big data research has emerged as a better option for obtaining useful information from the massive amount of data generated from the AM processes. Big data analysis also assists designers and engineers by collecting valuable information from clients and customers. Bi et al. (Ref 70) summarized the existing literature on AM, Big data, and how big data methods can offer a better future for AM technology. Further, their study briefed recent developments in AM technology combined with the IoT, cloud, and cybersecurity. Finally, their study finds scope for AM data unification and smart AM production process.

IoT is a network of physical objects (things) embedded with sensors, software, and electronics to initiate the collection and exchange of data and information. By integrating AM and IoT superior product quality, less production waste, better product and process analysis, actionable feedback for product and process improvement, and reduction of set-up costs, errors, and machine downtime can be achieved (Ref 69). IoT with various sensors collects real-time data for different operating parameters and assist in the optimization of AM methods for better product quality with the use of sophisticated digital techniques.

In recent years, a group of researchers working on combining the techniques of smart manufacturing, sustainable manufacturing, and additive manufacturing to make a unified term of sustainable and smart additive manufacturing (SSAM). Majeed et al. (Ref 71) proposed big data-driven sustainable and smart additive manufacturing (BD-SSAM) for the benefit of the additive manufacturing enterprises. The proposed system could be useful to know the beginning of life (BoL) stage of the product life cycle. Their experimental results found effective control over energy consumption and product quality with BD-SSAM in the era of smart sustainable and cleaner manufacturing. The proposed BD-SSAM framework was used to manufacture AlSi10Mg alloy pimp components using the SLM system. BDA with the other algorithms was used to optimize the process parameters of SLM for better product quality, lower energy consumption, and higher productivity. However, the proposed BD-SSAM framework was applied only on the BOL stage of the product life cycle due to the available resources and

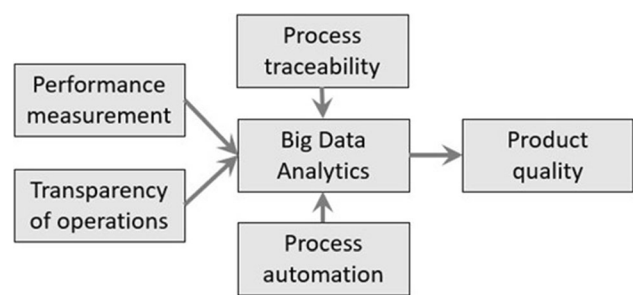


Fig. 8 Big data analytics to enhance AM product quality (Ref 69)

configuration of IoT devices in the company. The authors find scope for further research on the application of this framework on the whole lifecycle stages, and the development of the algorithms to optimize the processing parameters for various AM techniques and multiple materials.

Wang et al. (Ref 72) investigated the current development of AI-enabled AM product development and future perspectives. Their study reviewed the current research activities on the application of AI in AM, including product design, process design, production, and services. Several research gaps with future directions were summarized. Ashima et al. (Ref 73) explored the requirement for industry 4.0 technologies for AM processes and the advantages of the application of information technologies (IT) in AM. Further, their study analyzed the benefit of integrating the IoT and AM techniques to the industries and material manufacturers. Their study concluded that IoT application in AM improves the efficiency of production processes followed by reduced manufacturing waste and fulfilled customer specifications.

Arkadeep Kumar (Ref 74) reviewed the existing methods and material technologies for smart manufacturing, such as the IoT, cyber-physical systems, human–robot interaction, augmented and virtual realities with their challenges. Agrawal et al. (Ref 75) analyzed the drivers for integrating industry 4.0 with AM, which were prioritized using multi-criteria decision-making (MCDM) technique, namely analytical hierarchy process (AHP). Their study observed cloud computing and manufacturing as the topmost driver, followed by high-throughput AM systems and collaborative manufacturing. The highest priority for cloud computing and manufacturing could be attributed to their several online services to AM technologies. The second-highest priority for high-throughput AM systems could be attributed to their potential to fabricate complex, intricate, and any imaginable part within a short period.

From the literature review, it has been understood that AM, BDA, and the IoT are crucial technologies of Industry 4.0. The integration of these technologies is likely to change the manufacturing world in a big way in the coming years. Big data is simply too large and complex data that requires a set of tools and techniques for analysis to gain insights from it. The size of the datasets, pricing of the tool, kind of analysis to be done, etc., are some of the parameters for the selection of the right tool and technique. AM presents a “Big Data” challenge. AM generates huge data while printing and in-situ monitoring a component. BDA is one of the fastest evolving fields due to the convergence of the IoT. In-situ monitoring and BDA for AM are important research topics. The authors observed the research on BDA in SSAM is still in its early stages and needs further studies to overcome several key challenges.

## 4. Design for Additive Manufacturing (DfAM)

Design optimization using topology optimization and GD techniques assist in reducing mass and hence savings in materials. Design optimization also enhances aircraft efficiency by reducing energy and transportation costs. AM has increasingly been used for many engineering applications for reducing mass and product development time (Ref 76–78). Topology optimization which structurally configures the products has been considered as one of the most effective and powerful

design tools in aeronautics and aerospace engineering for weight reduction and performance design. GD technology assists engineers in dealing with several design objectives such as minimizing the weight of parts, cost reduction, maximizing the stiffness, and the optimum usage of material. The following sub-sections discuss topology optimization and methods for generative design for weight reduction and manufacturing of products with high resolution.

### 4.1 Topology Optimization

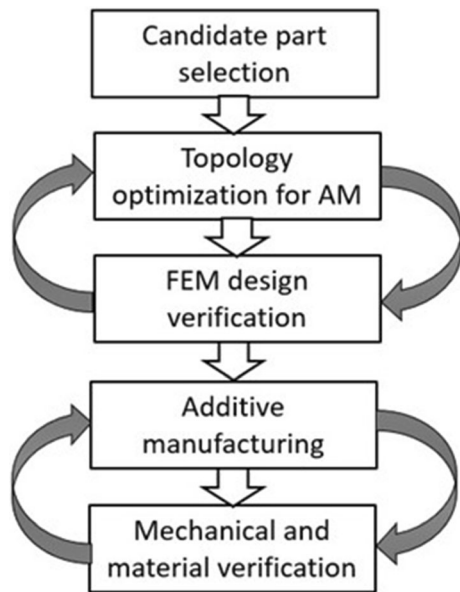
Topology optimization techniques are effectively used in layout design for airframe structures, stiffener ribs for aircraft panels, multi-component layout design for aerospace structural systems, and multi-fasteners design for assembled aircraft structures. Nowadays, topology optimization has become an integral process to better designing the AM process by minimizing support material and manufacturing time.

Meng et al. (Ref 7) demonstrated that how AM and topology optimization could be used synergistically for design and manufacturing through an illustrative example of the aerospace bracket. Their study reported that an Airbus A320 nacelle hinge bracket manufactured by the direct metal laser sintering (DMLS) process reduced the CO<sub>2</sub> emission over the whole lifecycle of the nacelle hinges nearly by 40% via weight reduction. Topology optimization being among the three sub-fields of structural optimization is mostly employed in the early stage of structural design. The other two are size and shape optimization. Structural and topology optimization brings together design and modeling techniques that have helped the aerospace industry to come with better low-weight aircraft components without compromising on their structural functionalities.

Zhu et al. (Ref 79) reviewed recent advances in topology optimization techniques, especially the application of density-based approaches in the design of aircraft and aerospace structures. Their study provides a valuable reference for researchers in structural optimization design and engineers in the aircraft and aerospace industries. Their study also emphasized challenges for the development of topology optimization for more demanding applications.

A holistic process flow as shown in Fig. 9 is generally followed to ensure reliable and repeatable additively manufactured aviation components. The process flow includes candidate part selection, topology optimization for AM considering design considerations, then finite element modeling for analytic verification, AM of the components, and lastly final verification of mechanical and material at component levels. Topology optimization for AM considers design considerations for the removal of support structures and powder. Further, topology optimization also considers the design of support structures for minimum residual stresses. Two separate feedback loops ensure about withstanding of the optimized design to the specified loading conditions and the mechanical integrity and performance of the manufactured components for actual working conditions they will be employed (Ref 80).

Topology optimization combined with AM technologies provides an effective approach for the development of light-weight high-performance structures. Shi et al. (Ref 14) designed a heavy-loaded aerospace bracket by topology optimization and additively manufactured using selective laser melting (SLM). Their study proposed thermo-elastic topology optimization considering mechanical forces and temperature



**Fig. 9** Holistic process flow for the fabrication of repeatable AM components (Ref 80)

loads and the sensitivity analysis was derived. An aerospace bracket was successively designed using topology and size optimization. The design space for topology optimization was firstly defined by extending the original geometric model of the aerospace bracket. The objective function of the topology optimization problem was defined as the minimization of global compliance. Further, the aerospace bracket was re-modeled by them based on the optimized structural configuration. Finally, the size optimization was carried out by them to achieve a final design of the aerospace bracket based on the reconstructed model. Their study observed a reduction in the mass of the aerospace bracket by 18%, benefiting from topology and size optimization. Their work concluded that the design of structures under thermal–mechanical loading could be effectively designed by integrating thermo-elastic topology optimization with AM technologies.

Kamal et al. (Ref 81) discussed some key considerations on process aspects of design including material characteristics, part performance, and post-processing operations for AM part production. Their study also discussed cost factors related to AM part design and manufacturing. Trudel et al. (Ref 82) presented a new methodology for the design optimization of light and safe aerospace structures by combining topology, shape, and lattice material optimization techniques. Initially, a conceptual design was created using topology optimization, and then sizing and shape optimization methods were applied to reduce stress concentrations and obtaining even strain energy distribution. Finally, multiscale design optimization employing lattice materials was conducted based on the first stage design. A case study of an aircraft door hinge was presented by them that aims to minimize the weight subjected to a set of performance, material, and instability buckling failures constraints. Lattice material was incorporated into the final design. The material selected for an aircraft door hinge was titanium Ti6Al4V alloy. Their study observed a reduction in mass of about 44% for a simple aircraft door hinge with lattice material optimization. However, their study pointed out the limitation of the proposed model that the entire optimization process is to be

repeated if the topology optimization model gets updated as the resulted lattice optimization models may not be useful.

Berrocal et al. (Ref 83) used the topological optimization methodology to redesign connector support of the VEGA space launcher, a typical lever component from civil aircraft and housing part from fan cowl structures. For the connector support and the lever optimization, the weight reduction observed up to 63% and 32%, respectively, fulfills the stress requirement. The housing optimized design reached weight reduction up to 19% with a maximum stress value of 489.8 MPa against the material yield stress of 1013 MPa. Their study showed that a larger weight reduction could be achieved by reducing joining (rivets) interfaces with a similar maximum stress value.

Hybrid additive-subtractive manufacturing (HASM) which combines advantages of both AM (complex part manufacturing) and subtractive machining (better surface precision and dimensional accuracy) is being increasingly used. However, very few studies attempted on the topological optimization for HASM. Han et al. (Ref 84) proposed a geometry approach method for topology optimization of continuum structure using the bi-directional evolutionary structural optimization (BESO) method. Their study simultaneously considered both AM and subtractive machining constraints during each topology optimization iteration. Their study observed better surface quality and machining accuracy with HASM.

HASM also requires further research on HASM-related constraints, such as residual stress/strain induced by thermal stress, manufacturing defects, inter-layer fusion, and milling. It is also reported to have further work on coupling the proposed geometry approach method for topology optimization with methods for finding the optimum build direction and applied to complex structural surfaces (Ref 84).

The design of the thermo-elastic structure in the aerospace and the power engineering fields has undergone extensive research and still needs attention as a compromise to be reached between the minimum structural compliance and the maximum strength. Further, it is suggested to develop advanced topology optimization methods for multifunctional and monolithic products. Also, emphasized further research in the multiscale topology optimization wherein the macrostructure to be optimized concurrently with local materials at the microscopic scale (Ref 5). Jihong et al. (Ref 85) reviewed the literature available on the integration of topology optimization and additive manufacturing. Their study observed that the integration of material, structure, process and performance is important to pursue high-performance, multi-functional and lightweight production.

From the literature review, it is understood that topology optimization assists designers in exploring a much larger design space being a freeform material distribution scheme for structural design. The designers could create, merge, and split the interior solids and voids during the structural evolution. Often AM parts need subtractive machining as a post-process for obtaining a better surface finish and close dimensional accuracy. However, AM component designed using topology optimization often makes post-machining difficult and expensive due to the complexity of geometry. Hence, there is a scope for obtaining an economical, machining-friendly topological design for AM parts, and that could be obtained by developing smart design algorithms. There is enough scope for further studies on topology optimization considering material and manufacturing uncertainties and geometric nonlinearity.

Sufficient studies are reported on topology optimization for functionally graded and multi-material parts. However, studies are required on the complexity of the interface distribution and grain size and porosity distribution in AM processes for metals. From available studies, it is seen that integrating topology optimization with AM, has wide applications in modern manufacturing. However, structural optimization is still a hot issue and needs further studies, especially in the case of AM of functionally graded materials.

#### 4.2 Generative Design (GD)

In recent years, it has become possible to explore the design space for multiple objectives considering multi-disciplinary requirements with the advent of generative design for additive manufacturing (G-DfAM). GD is a part of the family of DfAM techniques that compare and consider a multitude of design outcomes in several technical fields. G-DfAM provides the most desirable outcome, light-weighting with the increase in the performance and functionality of the parts by ensuring the correct design into the right manufacturing technology. The G-DfAM has resulted as an effective way to predict, analyze, and design AM processes.

Advanced GD software is enabling engineers to optimize aerospace designs to benefit in specific from AM processes. These improvements can reduce the life-cycle cost of the plane by increasing engine efficiency, reducing drag, and reducing mass (Ref 13). The GD tools offer the best-optimized parts or assemblies with computational power and optimization techniques (Ref 86). Attempts have been made in combining a set of frameworks and directives or rules (commands to the designer) for designing using evolutionary algorithms (Ref 87).

G-DfAM provides the most desirable outcome, light-weighting with the increase in the performance and functionality of the parts by ensuring the correct design into the right manufacturing technology. With this technology, it is possible to add or remove material wherever needed or not necessary. Thus, the process is a repetition of potential outcomes that comply with certain constraints, boundary conditions. The designers attempted to obtain the best solution for low weight, time for build, and cost by changing different inputs. G-DfAM emerged as a reliable and fast method of finding design possibilities in various design fields (Ref 88).

A group of researchers attempted to reduce weight and cycle times while AM of aerospace components using generative design techniques. Guanghai et al. (Ref 89) performed topology and size optimization for mass reduction of a heavy-loaded aerospace bracket. Their investigation found a reduction in the structural mass of the aerospace bracket by 30% with satisfying all mechanical performance criteria. Briard et al. (Ref 90) applied generative design methodology for designing a seatbelt bracket. Their study proposed a generative design workflow to confront different software and techniques. Their study pointed out the scope for future work to improve the proposed method by implementing new use-cases. Moreover, their study emphasized further research on the integration of upcoming innovations related to progress in generative design and AM.

Tutum et al. (Ref 91) proposed methodology for discovering new designs of consumer-grade printers which can be generalized to other functional design problems. The proposed methodology consists of three components: First, an effective search space is learned through a variational autoencoder (VAE); second, a surrogate model for functional designs is

built; and third, a genetic algorithm is used to simultaneously update the hyperparameters of the surrogate and to optimize the designs using the updated surrogate.

From the available limited literature, it is understood that generative design provides designers and manufacturers a much higher range of design options to select the best suitable design option considering the key design constraints. Moreover, in G-DfAM, the manufacturing process capability and constraints are considered when the concept is being developed rather than working on them after the concept development. Attempts are made in integrating ML for topology optimization and applications of BDA to topology optimization. However, the authors observed almost no studies on applications of ML techniques and BDA for G-DfAM.

Design using generative methods generates the finished design autonomously. GD is emerging for rapidly generating design concepts and obtaining multiple solutions to those concepts. However, its successful implementation for different AM processes needs immediate attention to its computational cost and the need for post-processing at various steps in the process. Available studies show that the prospects brought by GD are not explored enough. Some studies attempted small component design, but very few cases were reported from aeronautics.

#### 4.3 Modeling and Simulation

In metal AM, components are susceptible to complex microstructures and residual stresses due to the deposition of heated mixtures of particulate materials onto surfaces and then subsequent bonding and cooling. AMed component properties are significantly affected by the material's microstructural characteristics. It is inevitable to know the behavior and properties of the AMed materials or parts beforehand to certify them for aerospace components. Simulation and modeling techniques are employed to understand the parametric effect on the performance of the AM process and the product used.

Modeling and simulation of AM assist in knowing microstructure and residual stresses considering the effect of process parameters. And having prior knowledge of the material behavior through simulation and modeling plays a vital role in AM, especially for Aerospace applications (Ref 92). The AM modeling approach can be analytical, numerical, or empirical. The temperature distribution during process significantly influences the microstructure, distortion induced by residual stresses, and fatigue properties. Figure 10 shows the different areas of modeling and simulation in AM processes.

Allevi et al. (Ref 94) performed a feasibility study of the thermoelastic stress analysis on a titanium-based-alloy space bracket made by electron beam melting (EBM). Their study needs further attention to compute residual stresses in AMed components. Hosseinzadeh et al. (Ref 95) assessed product quality using multi-physics computational algorithms during direct laser deposition of carbon steel. Their study simulated the thermal stress, deformation, and austenite grain topology varying the scan speed, laser power, and injection rate of metal powders. Their study observed von Mises stress and thermal history significantly affected by the rate of metal powders injection, laser power, and scan speed. The increase in von Mises stress was observed with the increase in the scan speed and laser power. Their study observed non-uniformity in the microstructure of the printed part and a change in the size of the heat-affected zone with higher scan speed.

Bonifaz et al. (Ref 96) developed a finite-element thermo-plasticity model in the wire arc AM process in a three-dimensional domain. The multi-layer deposition on plastic strains and thermal stresses was investigated. Their study observed an increase in thermal stresses and local plastic strains with an increase in the welding speed and the heat distribution parameter. However, the heat distribution parameter was more significant in the case of thermal stresses. Bhandari et al. (Ref 97) developed a fast, reasonably accurate, continuum finite element model for predicting the linearly elastic structural response of the 3D-printed cellular structure. The micromechanics homogenization approach was extended to homogenize 3D-printed partial infill cellular structure properties. However, the continuum model generated is valid only for a linearly elastic structural response.

Jeong et al. (Ref 98) proposed a new method to effectively implement the thermal analysis for process simulations of laser powder-bed fusion (L-PBF) technique using ABAQUS software. Thermal analysis for simulations of AM process is performed, and the melt pool size is compared with test results to verify the accuracy of the simulation. Their study implemented user-defined subroutines and field variables to correctly track the temperature history of each integration point for the finite element analysis and hence, to assign appropriate material properties.

Chen et al. (Ref 99) proposed an advanced fuzzy approach to forecast the yield for aircraft parts using three-dimensional (3D) printing. Their study addressed a crucial problem in yield forecasting using the logarithmic or log-sigmoid value instead of the original yield value to simplify the computation. Zohdi et al. (Ref 100) simulated cooling-induced residual stresses in heated particulate mixture depositions in additive manufacturing. Their study aimed to develop a computational framework that is relatively easy to implement to analyze deposited hot particulate microstructures undergoing cooling. Their study developed a recursive, staggered, temporally-adaptive, finite difference time domain model considering the elasto-plasticity and damage.

WAAM produces large parts with a higher deposition rate with respect to other AM technologies. However, WAAM

components are affected by severe distortions and residual stresses issues. Researchers attempted such issues efficiently using finite element process simulation. A group of researchers attempted modeling of WAAM process based on a novel heat source model that takes into account the actual power distribution between filler and base materials (Ref 101). Attempts were also made to a 3D transient mathematical model to simulate the heat transfer, fluid flow, and geometry morphology in GMAW-based WAAM. Zhao et al. (Ref 102) performed the simulations of single-pass multi-layer of WAAM of Al-5%Mg by coupling the processes of droplet formation, growth, and detachment from the end of wire electrode with molten pool.

Most of the researchers simulated the solidification process of L-PBF using Computational Fluid Dynamics (CFD) software and computed resulting residual stresses from solidification using FEA software. From the studies, it is understood that the fusion depth is largely affected by the laser power, scanning speed, spot size, and residual stresses in the parts significantly influenced by the melt pool dimensions. Further, the dimensional accuracy and distortion of the part can be controlled by properly selecting the laser power and the bed temperature for the material to be processed.

Attempts have been made to model heat-affected zone (HAZ) dimensions and predict the mechanical properties of the part. It is seen that laser power, scanning speed, laser beam velocity, and laser spot diameter are very crucial in obtaining minimum HAZ and better mechanical properties. A group of researchers has made an attempt to model surface finish and microstructure formation for DED. They found laser power, scanning speed, stand-off distance, and powder feed rate are the prominent parameters for obtaining a better surface finish. On the other hand, in SLM powder layer thickness, laser power, scanning speed, and heating of base plate were reported as significant process parameters for limiting the residual stresses, porosity, and surface roughness.

Sufficient studies investigated the L-PBF, DED, and SLM process dynamics considering the effect of scan velocity, powder-layer thickness, scan spacing, and laser power. However, limited studies are available on the Electron Beam

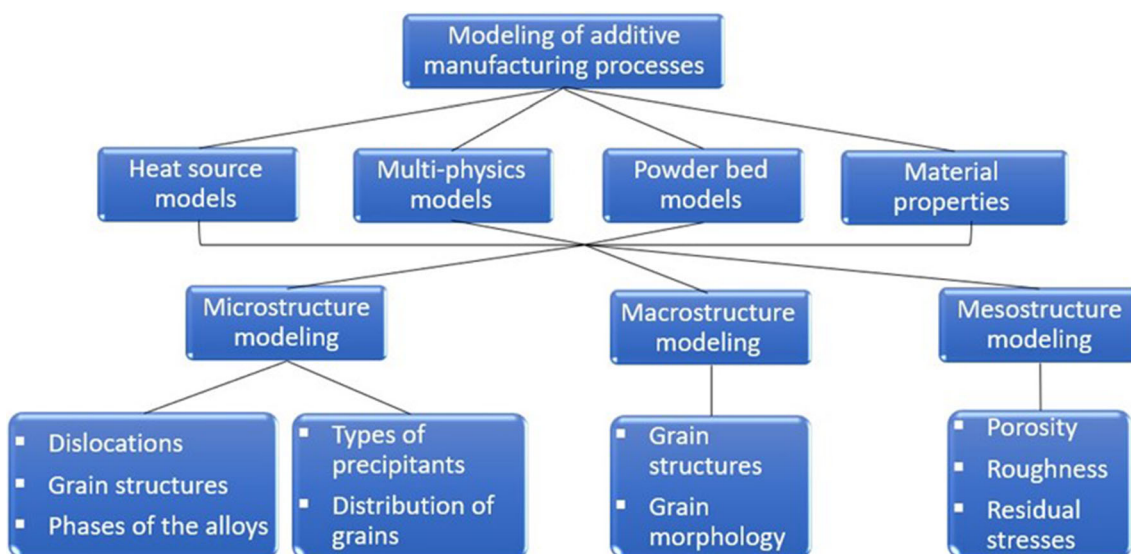


Fig. 10 Different areas of modeling of AM processes (Ref 93)

Melting (EBM) process. Studies reported on EBM mostly attempted thermal modeling and predicted melt pool dimensions and found beam power, beam scan speed, beam diameter, and beam current as the significant process parameters affecting the process responses.

## 5. AM: Challenges and Scope

AM technologies have shown great potentials to reduce weight, increase design features, improve fuel efficiency, and reduce manufacturing times for aerospace applications. However, a substantial gap exists in the application knowledge and practical implementation for various commercial products in the industry (Ref 103, 104). Mismatch in material properties and dimensional accuracy, and surface finish of the printed part are major concerns. It is very much possible for AM of special steels, titanium alloys, ceramics, and nickel alloys. But there is an immediate need for availability of standard material characteristics database for these materials for AM industry. There is also a need to develop physics-based models to understand beforehand the material properties (strength, fatigue, etc.) for these materials as they work in extreme conditions.

Metal 3D printing technology is commercially available. But further studies are required to have better control over the quality of the printed component, the alloy microstructure, surface roughness, porosity, distortion, and residual stress for better mechanical properties of the printed products. Design using generative methods generates the finished design autonomously. However, it still requires the skill and artistry that encompasses different design methods, and very little is explored for aerospace applications. Limited studies attempted deep learning techniques in-process monitoring for AM of aerospace components.

Studies pointed out that there are still unknown details of the molten pool shape and the material transfer physics that will influence the successful implementation of the AM process (Ref 105). There are still gaps in the AM knowledge base that needs extensive research work. Sustainable and smart additive manufacturing (SSAM) is picking up by the aerospace industry. However, the development of the algorithms to optimize the processing parameters is required for various AM techniques and multiple materials. The authors found a substantial potential in the field of hybrid manufacturing (subtractive and additive) technologies to explore in the future.

DL requires sizeable datasets to predict unseen data and to train the models and one needs to find out the way when real-time data processing is required or when the provided datasets are limited. Transfer learning and data augmentation have been researched over the last few years to address this issue. Attempts are also required to use models with semi-supervised and unsupervised learning to manage practical data without the need for manual human labeling. There is also scope for utilizing cloud computing that offers a solution to handling the enormous amount of data with increase efficiency and reduce costs (Ref 106).

One needs to address the major concerns of AM, such as anisotropic mechanical properties, the building of overhang surfaces, high costs, low manufacturing efficiency, warping, and limitation on the use of materials to make AM technology the first choice for real-world applications. (Ref 107). Aero-

space components during their service life undergo corrosion, local impact, thermal cycles, fatigue, etc. These conditions lead to defects, distortions, cracks, and fractures in the component. Hence, repairing and remanufacturing are employed to restore components to workable conditions. DED is mostly used for repairing and remanufacturing as it offers high precision, low part distortion, narrower melting, and Heat-Affected Zones (HAZ). A group of researchers attempted repairing and remanufacturing studies on various damaged aerospace components using DED (Ref 108-111). However, further studies are required on the mechanical properties and the microstructure of the repaired parts, the feasibility of using different materials to repair the components, and repaired part interface.

BAAM is changing the way large parts are made for various worldwide applications. BAAM created new possibilities in material testing and various manufacturing applications. BAAM has the potential to manufacture components of considerable size in a single print run and more cost-effectively, which otherwise require higher manufacturing costs and longer lead times. However, BAAM is still a niche technology, and it still needs to be fully explored to overcome manufacturing challenges while producing larger parts.

## 6. Conclusion

Additive manufacturing (AM) has emerged as a promising technology to cater to the increasing demand for the fabrication of multi-functional, multi-material, and complex aerospace parts. AM generates massive amounts of data during manufacturing that need to be collected and analyzed for better AM performance through cost-reduction. AM with the use of artificial intelligence, the Internet of things, big data analytics, process simulation modeling, and cloud computing technologies assist in increasing product reliability. The present work reviewed comprehensively the literature available on the AM processes for aerospace applications considering machine learning and deep learning techniques, big area additive manufacturing, topology optimization, generative design, knowledge-based process planning, big data analytics, Internet of things, and process simulation modeling for aerospace components. Finally, challenges and scope for further research in algorithmically driven AM processes for design and production of aerospace components are presented. Following conclusions could be drawn from the present review.

- Machine learning (ML) techniques are widely used in the AM of aerospace components to make them cheaper, faster, lightweight, and energy-efficient. With these techniques, the product development lifecycle of aerospace components reduces drastically. These techniques find increasing applications in AM process design, optimization, in-situ process monitoring and controlling, and developing a cost-efficient laser powder bed fusion process.
- Deep learning (DL) architectures, namely deep autoencoders, long short-term memory, convolutional neural networks, deep belief networks, and some of their hybrid forms, are mostly used for diagnosis, anomaly detection and prognosis in parts of the aircraft. It was observed that DL models often outperformed model-based and statistical ML techniques. However, comparatively few studies have been attempted using DL techniques in AM of aerospace

components.

- Big area additive manufacturing (BAAM) is emerging as an economical and flexible solution for manufacturing large parts and components. However, BAAM needs to be fully explored to overcome manufacturing challenges while producing large parts.
- Hybrid additive-subtractive manufacturing (HASM) is increasingly being used. However, few studies attempted the topological optimization for HASM. Further research is required on HASM-related constraints, such as residual stress/strain induced by thermal stress, manufacturing defects, and inter-layer fusion.
- Advanced topology optimization methods for multifunctional and monolithic products need to be developed. Generative design (GD) for AM provided light-weighting with the increase in the performance and functionality of the parts by ensuring the correct design into the right manufacturing technology. Advanced GD software is enabling engineers to optimize aerospace designs that reduce the life-cycle cost of the plane by increasing engine efficiency, reducing drag, and reducing mass. However, generative design still requires the skill and artistry that encompasses different design methods. Available studies show that the prospects brought by GD, especially for aerospace applications, are not explored enough.
- By integrating AM and IoT, superior product quality, less production waste, better process analysis and feedback, and reduction of set-up costs, errors, and machine downtime, can be achieved. Modeling and simulation of AM assist in knowing microstructure and residual stresses considering the effect of process parameters. Sufficient studies investigated the SLM process dynamics considering the effect of scan velocity, powder-layer thickness, scan spacing, and power. However, limited studies are available on the Electron Beam Melting (EBM) process.
- Sustainable and smart additive manufacturing is picking up by the aerospace industry. However, the development of the algorithms to optimize the processing parameters is required for various AM techniques and multiple materials.

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