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Process–Defect–Performance Relationships in Additive Manufacturing of Aerospace Alloys: A Critical Review of Advances and Challenges

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Abstract: Additive manufacturing (AM) has advanced considerably as a disruptive technology that addresses the increasing demand for multi-functional, multi-material, and geometrically complex components and has begun to reshape areas of both product development and production methods. However, significant challenges related to incompatible material properties, defective parts made from AM processes, and inconsistent use of product build quality still exist. The ability to achieve highly precise AM processes is heavily reliant on monitoring, controlling, and utilising multiple process variables effectively. In recent years, more advanced methods, including machine learning (ML), big data analytics, and design for additive manufacturing (DfAM), have become more available to address these limitations. Although these methods have been studied significantly, their use in aerospace-specific settings has been limited. In this review, the study first provides an in-depth discussion on contemporary trends in DfAM. The review also considers simulation and modelling tools as enablers to obtain improved geometric fidelity in AM and to increase the predictability of AM processes. Other trends include improved automation through the IoT, as well as knowledge-based process planning, also for multi-part cases of production. Lastly, the review summarises many of the ongoing issues and some future directions for algorithm-driven AM in aerospace and relates to industry 4.0 trends that emphasise intelligent automation, adaptive process control, and lifecycle management, which will improve efficiency, reliability, and scale-up of AM technologies in aerospace and other advanced engineering applications.

Keywords: Additive Manufacturing, Aerospace, Big Data Analytics, DfAM, IoT, Machine Learning.

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1. Introduction

Manufacturing processes are constantly evolving towards the production of new products with stringent technical specifications. One of the modern technologies is additive manufacturing. The potential of AM has been around for a few centuries. Through the collection of data from a computer model, additive manufacturing (AM) can create the object or product incrementally, starting from the lowest layer until it forms a 3-dimensional object. AM, as an alternative to manufacturing processes, offers unique benefits for the manufacturing of customised products. This allows complex geometries at a macro, meso, or micro scale [1]. There are renewed applications of AM in many key industries, such as aerospace, automotive, and medical fields. AM remained predominantly in aerospace component applications, with about 18.2% of the global industry market share in 2017 [2-6]. AM optimisations can effectively be realised using topology-based geometry components in complex ways compared to the manufacturing process. A team of researchers has proposed an integrated decision-support system for AM production and distribution planning [7-9]. This process produces near-net-shaped parts that typically yield nearly one “buy-to-fly” ratio. The classification includes material extrusion, sheet lamination, powder bed fusion (PBF), binder jetting, directed energy deposition (DED), material-jetting, and photopolymerization. For various processes, DED and PBF are the most common methods used in the aerospace industry, with metal AM contrasted to photopolymerization [10]. The critical attributes of AM in clinically replacing products in the aircraft industry are shown in

Fig. 1. by properly aligning “critical attributes” with the aircraft industry, many of the inventory and supply chain issues could be resolved. Singamneni et al. [11] present the state-of-the-art of AM for the aircraft industry in relation to hurdles and acceptance for the future. The authors focused on a systematic, quantitative literature review to examine the areas of existing research and any gaps in the literature. The process the authors employed to develop perspectives from the published literature can be seen in their systematic literature review process in Fig. 2.

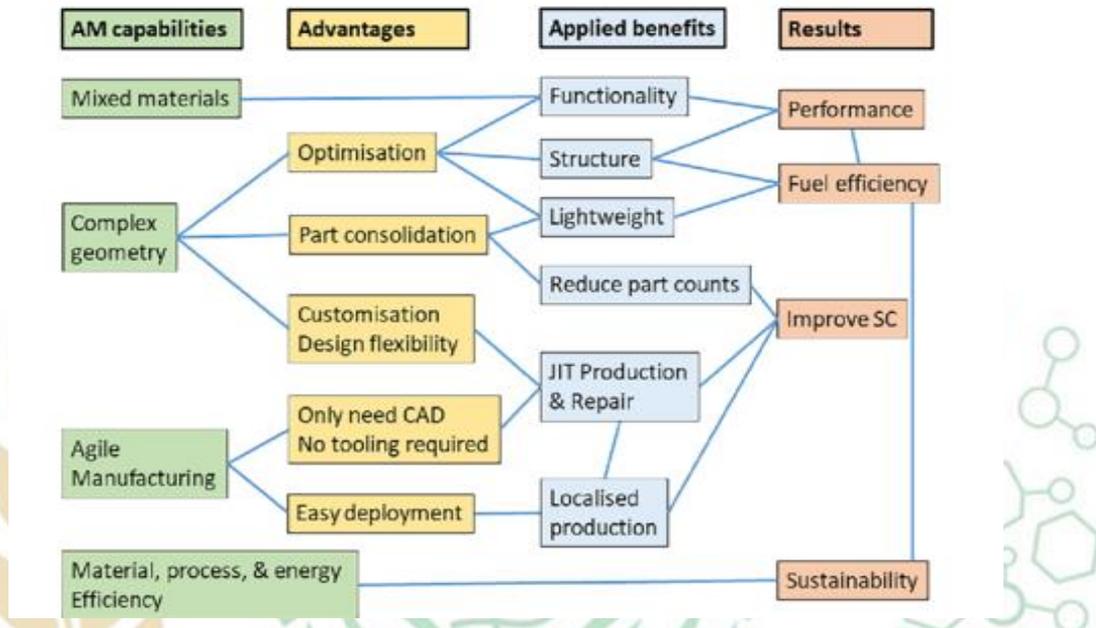


Fig. 1: Additive Manufacturing: Capabilities, Advantages, Benefits, and Results [11]

More recently, it has been demonstrated that effective designs for high-performance structures can be obtained from topological optimisation with AM [12]. During the DfAM phase, the primary structural optimisation tools are topology optimisation and GD. GD allows the comparative study of many “design outcomes of the aerospace parts” design process that have complex manufacturing process steps, such as blades, valve bodies, airfoils, etc.

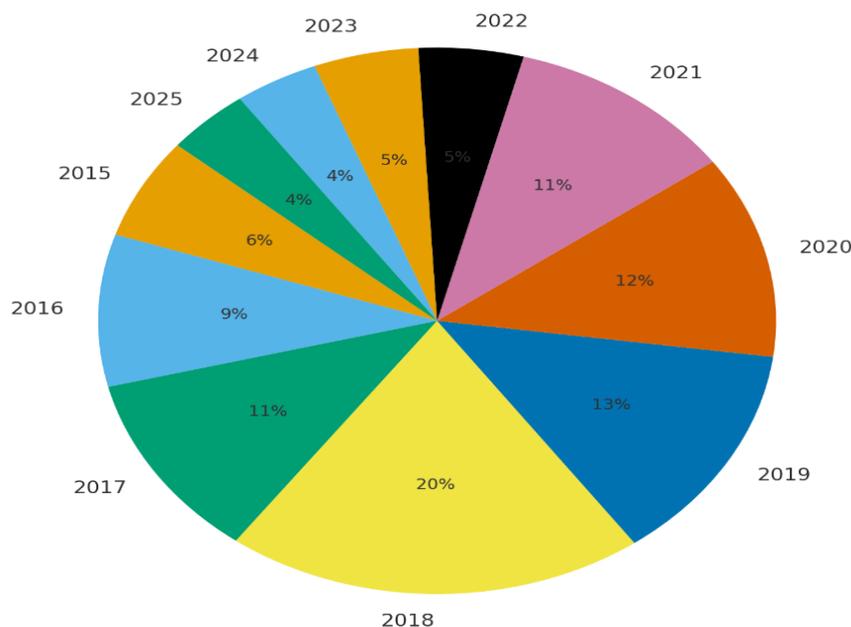


Fig. 2: Systematic Screening and Selection Process of Review Articles

The developing advanced generative design software chambers engineering practice works to optimise the aerospace design while also leveraging the unique benefits provided through the AM process [13]. The innovative design of the aerospace components enabled a mass reduction of approximately 50%-60% using topological optimisation and AM to manufacture the part [14]. This is also a data-intensive field that allows researchers to use various ML techniques to conduct research. A group of researchers attempted projects that brought ML techniques and AM together in studies on ML for enhancing product quality, detecting, and predicting different defects and distortions during the manufacturing process, optimal process times, and reduced costs [15]. Table 1 shows the process planning to-do items in the AM domain concerning the part orientation for varying levels of dimensional inaccuracies [16-18].

Table 1: Summary of Machine Learning Applications and Neural Network Frameworks in Additive Manufacturing [17]

Focus Area	Input Features (X1...Xn)	Output (Y)	ML/NN Structure	Key Contribution
Taxonomy of ML applications in AM	Various input characteristics (process parameters, material properties, geometry features)	AM process outcomes (defects, performance, reliability)	Generalised ML framework (taxonomy-based)	Classified diverse ML applications in AM with input-output mapping
Neural Network Architecture for AM	Input vector (X1...Xn)	Output prediction (e.g., quality, defect detection)	Fully connected NN: 1 input layer, 2 hidden layers, 1 output layer	Demonstrated NN design for AM, highlighting activation functions and weighted connections

All major exertions are identified in understanding opportunities for better product design and material attributes for AMed components through simulation and modelling. It aids in establishing the process parameters for AMed components that possess no defects and are distortion-free. Researchers have attempted to repair aircraft components that are prone to cracking and distortions due to varying thermal stresses, temperatures, and corrosion using AM and cladding processes. Researchers are also taking initiatives in the “big area additive manufacturing (BAAM)” for large-sized aerospace components to assist manufacturers in more cost-effective and faster production. This is emerging slowly as an affordable and flexible fabrication solution for generating large parts and components. Over the past decade, extensive research has been conducted in the area of BAAM fabricating large products [19]. The authors indicated that a review of some literature in recent times shows sufficient attempts made by the researchers in reviewing additive manufacturing processes for aerospace applications.

Research efforts in the field of DfAM and topology optimisation have primarily concentrated on strategies for designing and redesigning components for both direct and indirect AM fabrication. These studies frequently highlight how topology optimisation can be coupled with AM to maximise material efficiency while maintaining structural integrity. By contrast, broader review studies on additive manufacturing itself have largely emphasised its industrial applications, particularly in aerospace [20]. Such reviews underline the advantages of AM, including lightweight structures, design flexibility, reduced material waste, and cost-effectiveness, as well as the growing adoption of metal AM technologies for aerospace structures. More recently, attention has expanded beyond design and

applications to include monitoring, process control, and data-driven approaches. Several studies have investigated the role of process monitoring, BDA, and IoT in ensuring quality and reliability in AM processes.

These studies frequently emphasise inspection methods, both in situ and post-process, capable of discovering defects or deviations in real time, thereby decreasing failure rates. Comparative studies were also utilised to judge the performance of ML methods in the field of AM, which provides important insights into the most effective ML methodology. Even more, in the last few years, there has been a growing focus on incorporating ML and DfAM or AI-enabled product development. Researchers have demonstrated that ML will optimise the parameters and geometry of AM parts and improve surface finishes, dimensional accuracy, and defect formation. Additionally, several reviews have explored the recent push for DL techniques and research that describe DL architectures' unique features. CNNs, specifically, have received much attention on account of their abilities to analyse large datasets, which include image-based monitoring of AM layers to predict or classify defects. There have been other DL methods studied, including autoencoders and a combination of these models for inspection of aerospace parts and quality verification. This review addresses both trends, such as big-data analytics and IoT-based methods for AM systems, focusing on defect detection, dimensional reliability, mass reduction, and yet, mechanically reliable structures. This review also addresses the higher potential of Deep learning-based frameworks to not only predict defects and turbine monitoring processes, but also to develop new optimisation algorithms based on material properties for process conditions, and not to mention ignoring AM system capabilities. AM is still evolving as a disruptive technology in the aerospace domain and beyond.

Combining DfAM, ML, BDA, and IoT certainly represents a significant step toward developing multifunctional and reliable products, but as indicated in the review literature later on, more collaboration between these fields will be paramount. This review was undertaken to create a resource that aggregates knowledge for academia and practitioners, while clarifying the development and the emerging trends. Fig. 3 provides the framework for how this review was completed to produce a systematic and comprehensive review of published literature. The authors began with a "critical and constructive analysis" of the existing literature, including literature from available databases.

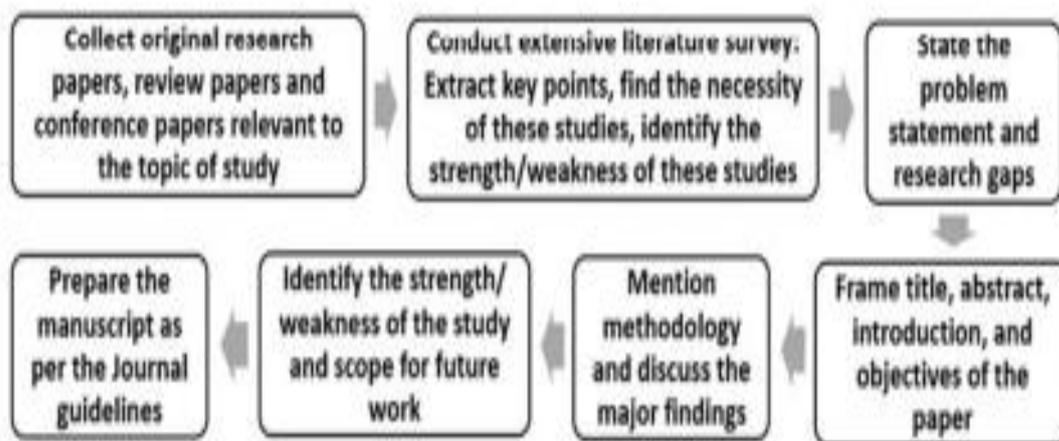


Fig. 3: Systematic Framework for Conducting and Categorising Review Studies [21]

The major portion of the research assessed was “21% of the total articles searched and 44% of the total research screened for eligibility to review”. The choice of study to critically review was based on identifying the most relevant and not older articles published in an indexed peer-reviewed journal and/or proceedings from a conference.

2. Machine Learning For AM

Artificial Intelligence (AI) is a well-established component of contemporary digital manufacturing [22]. The two most recognised and revered components of AI are ML and DL. These terms refer to algorithms capable of learning patterns from data to make predictions, while DL is a newer class of AI utilising multilayer neural networks that are capable of learning to extract features and intelligently make decisions without human input. DL has distinguished itself by demonstrating advantages with difficult, large, and complex data sets that are increasingly found in additive manufacturing (AM). In the article, the authors (see Fig.4) present a taxonomy of learning strategies for ML applications in AM, which supports the reality that the learning strategies of ML applications are vast. Within supervised learning, models are trained on a dataset that is labelled, which means the model has access to existing outputs along with existing inputs, thus allowing the system to learn the explicit mapping from one to another. This process is particularly useful for situations of classification or predicting material properties when there is experimental data available. Unsupervised learning has applications in the absence of output labels. For AM, clustering and principal component analysis are typically algorithms used to identify latent structures in the data or cluster parts based on geometric similarity or potentially estimate manufacturing costs [23]. Reinforcement learning allows algorithms to engage with the environment through trial-and-error learning and periodically maximise performance through a reward signal. Semi-supervised learning involves learning about the problem using features of both supervised and unsupervised learning, an unlimited pool of data not labelled, which is beneficial for AM, where there can often be limited to no high-quality annotated data available [24]. The aerospace sector led the implementation and application of ML within the AM community, driven significantly by the pursuit of lightweight, high-strength, and thermal-resistant parts. The reason for this is that aerospace materials are subjected to extreme operational conditions, creating a limited range of suitable engineering/structure materials that meet operational criteria and creating a management issue with developing and certifying new alloys and/or composite materials to replace existing materials is a rigorous, costly process that can consume a lot of time. Data availability and problem parameterisation are still issues, but the existing works lend themselves to a path that suggests that AI-based methods will certainly become the norm when it comes to the design/production of next-generation aerospace components.

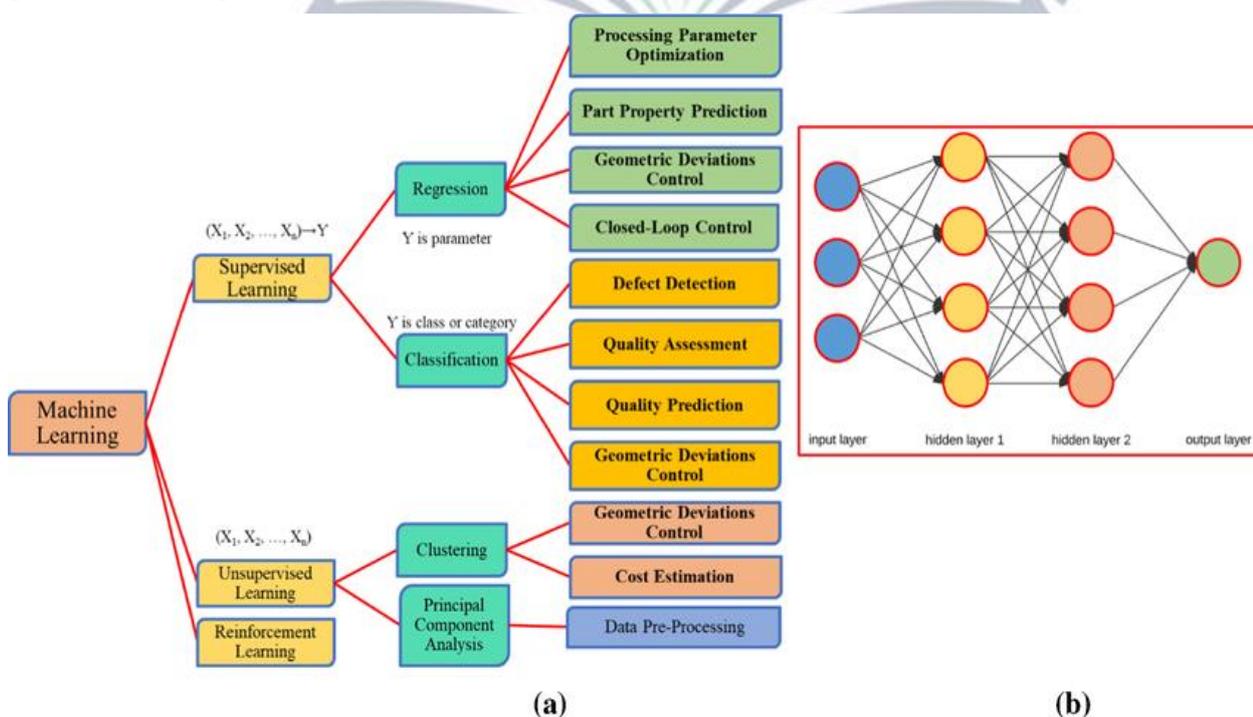


Fig. 4: ML Applications in AM: Input-Output Taxonomy & NN Structure [25]

2.1 AM Design and Process Optimisation

Recent developments in machine learning (ML) techniques have demonstrated substantial advancements in additive manufacturing (AM), providing capabilities to predict, monitor, and optimise these processes. In the aerospace sector, researchers have used basic geometric descriptors that describe the part along with artificial neural networks (ANN) to predict the production time for the part to help plan production. The research investigates the use of BNN to predict the surface quality of the part, as well as initiative-taking updates to the STL files during the printing of the part [26]. Convolutional neural networks (CNNs) have been used to design metamaterials, representing an unambiguous example of dealing with the themes of ML as applied to computational design at the level of properties [27]. This created a contemporary ML device, an easy-to-use app that assists new designers to reconfigure a design fit for the AM challenge and is an example of AM oriented ML device democratizing access to a complex design process and allowing a greater diversity of users to realise a sophisticated design [28].

In process optimisation, machine learning-driven parametric mapping is electrifying and has been applied to processes with discrete and flood approaches, i.e., DED, L-PBF, binder jetting, and material extrusion [29,30]. BNN models have been explored to predict the deposition height being deposited in DED [31,32]. Similarly, prediction of porosity in L-PBF is also an important quality prediction [34-39]. Gaussian Process Regression (GPR) has been explored to describe complex relationships with respect to melt pool dynamics [40]. In terms of fused deposition modelling (FDM), examples presented in this review also included neural networks with genetic algorithms to optimise digitised factors such as nozzle temperature, print speed, density, and infill density as example working problems with multiple measured and modelled input interactions.

2.2 In-Situ Process Planning and Monitoring

Although additive manufacturing (AM) allows some flexibility in the production process, challenges with planning, scheduling, and decision-making remain. Conventional approaches require a heavy reliance on experience to make the appropriate selection of process parameters, which can impact part performance, including microstructure, and dimensional and geometrical accuracy. Moving toward a more reliable manufacturing process could involve some automated-systems, or decision-support planning systems [40]. As AM becomes increasingly integrated into industrial manufacturing, the ability to make real-time decisions and adaptively control the process becomes even more important because it is during these adjustments that deviations can occur between AM and traditional manufacturing systems and can occur quickly [41]. Automating the detection and capture of data will allow AM production systems to react to unplanned contingencies more efficiently, which could alleviate risks associated with the interruption process. One area in additive manufacturing that has cost and labour implications for post-processing is the removal of supports after the completion of parts, especially for metallic parts. The use of an automated strategy, by a 5-axis machine, which departs parts into sub-volumes that were built without supports.

Fig. 5 depicts concepts of how a sensor unit (shown in green) could be integrated into the LPBF system of its operations. These concepts are meant to generate real-time information that relates to important process parameters, such as the behaviour of the laser melt pool, surface temperature gradients, powder distribution, and build surface quality. The idea of such integration is to embed sensors, either in or around the build chamber, to potentially enhance process control, detect anomalies as they occur, and provide a basis for closed-loop feedback. Enhanced real-time monitoring of these features is essential to ensure the quality of a part, data reproducibility, and reduced post-processing inspection effort of the part. The figure also signifies the importance of non-intrusive placement of sensors, so that neither powder flow nor the laser path is affected while ensuring a high spatial and temporal resolution is maintained. Ultimately, these concepts of integration will support the wider aims of DfAM of aligning the design of sensors to functional and environmental constraints of the AM process, while enabling

better manufacturing workflows using real-time data.

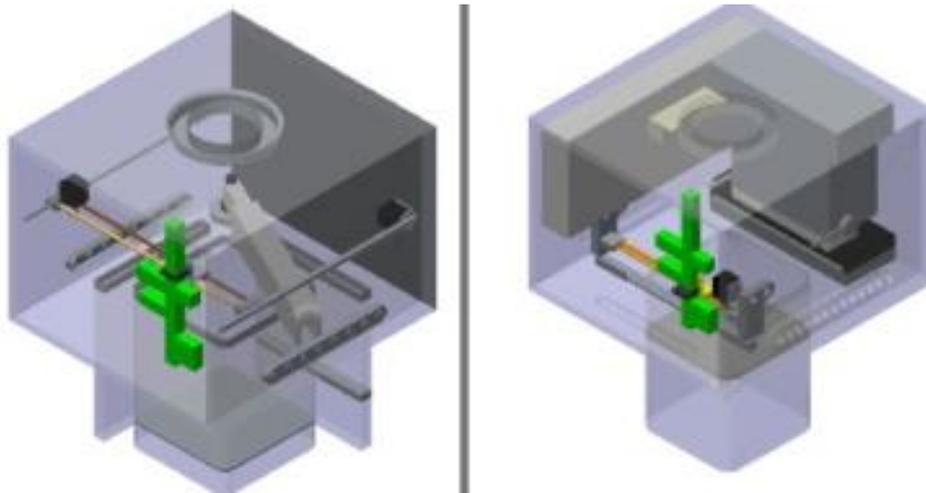


Fig.5: Integration of a sensor unit for in-situ monitoring of laser powder bed fusion [42]

Their experimental trials with decomposing and slicing supported their initial premise that constructions that utilised decomposed parts and slicing would have merit for hybrid-additive manufacturing processes. Relying on information from Xiao et al, hybrid processes can be defined as methods that combine AM with machining operations in alternating sequences, allowing direct digital manufacturing. Hybrid methods provide optimisation of build plate design (including placement of parts and orientation), as well as fixture setup, but there are yet to be studies that consider thermal implications on dimensional accuracy and tolerances of hybrid products [43,44]. Hybrid manufacturing faces a substantial disadvantage in collision avoidance between tools, parts, and nozzles. Chen et al. constructed deterministic methods for collision-free planning, and they used scheduling for hybrid process planning.

Together, these works represent paths to follow in future research opportunities regarding multi-axis hybrid systems. ML and DL technologies have taken centre stage in solving AM problems, especially in those where defects and process control are related. The AM processes, and more specifically, powder-based processes, such as L-PBF, tend to produce defects from the AM process in the forms of porosity, incomplete fusion, and dimensional accuracy defects [46–48]. ML-based schemes demonstrate useful predictive monitoring and corrective actions using sensor-based data. For example, Gaikwad, Aniruddha. [49] used in-situ optical monitoring of the print process to identify divergences that occurred during fabrication and subsequently execute corrective actions.

Advances in technology, including acoustic emission monitoring, provide further possibilities, as seen by Aydogan et al. [50] using CNN's to detect lack-of-fusion defects in L-PBF builds using sound-wave analysis. There is great promise for ML in the area of online—a closed-loop control of material extrusion processes, like FDM. A real-time adjustment of deposition parameters may help allow for changes in underfilled/overfilled locations in builds. Zhu et al. [51] developed a multifractal analysis framework that integrates with closed-loop control strategies to detect defects and inform predictive maintenance for the defects throughout the build layers. Ho [52] presented evidence, beyond the AM process itself, for using a data fusion method through CNNs and RCNs to predict pore development in the laser beam AM process through thermal history and infrared images. The study demonstrates the potential for DL methods, both from a practical standpoint and computational efficiency, as a useful method for defect detection in a real-time environment.

Additionally, broader reviews of relevant DL based literature continue to demonstrate the relevance and importance of these emerging technologies in aerospace maintenance and repair. Rahima et al. [53] noted the challenge of having any standardised datasets available to serve as barriers in

benchmarking defect detection and remediation method developments. Moreover, advanced models of neural networks, for example, DBNs and DQINNs, have shown potential to be beneficial for the diagnosis of defects within aerospace systems - in particular, fuel systems.

As discussed, DQINNs exhibited better accuracy and stability when compared to DBNs and DQNs, which also presented. Also, Bayesian Neural Networks have the potential to emerge as the next era of deep learning complexities in real aerospace applications. The utilisation of machine learning and deep learning continues to grow within the growing area of monitoring. metrics (e.g., machine learn, deep neural networks, deep learning) in both the additive manufacturing and aerospace sectors. Lei et al. [54] discussed Aeroengine vibration predictions and mitigation through a long short-term memory (LSTM) network along with an ACO approach. Positive results were stated, and robustness increases were stated regarding adaptive parameter learning. There were also positive results from research that utilised combinations of machine learning architectures (e.g., CNNs, LSTMs, Stacked Denoising Autoencoders, SVMs, DBNs, and multi-objective ensembles of deep belief networks).

Although some progress has been made, challenges still exist. For instance, dealing with the enormous amounts of data developed during AM processes will necessitate computationally efficient ML frameworks that can function on low hardware and in real time [55]. Data mining and machine learning (ML) can draw upon existing manufacturing knowledge to support the optimisation of fabrication methods and contribute to multi-objective optimisation across quality, cost, and time. In addition, creating production control systems that merge machine learning with cost administration could offer a practical way of enhancing the economic nature of production in a given context by quantitatively indicating how far deviations are, in monetary terms. This would provide industries with the capability to integrate part quality, safety, and financial performance more readily.

In summary, this profoundly changes additive manufacturing (AM) practices in aerospace applications, through predictive modelling, adaptive process control, and defect reduction. Machine learning provides useful, real-time monitoring ability; in contrast, deep learning allows for better precision in producing predictors for complex, high-dimensional data sets. As intelligent agents are integrated into AM workflows, the benefits would be improved part quality, lower waste, and higher reliability of the system. To obtain this potential will require future work focused on efficient real-time modelling and causal inference, as well as connecting decision-making with an economic framework in aerospace manufacturing.

2.3 Quality Control

Additive manufacturing (AM) has become a very disruptive manufacturing paradigm for high-value manufacturing industries like aerospace, defence, automotive, and biomedical engineering. AM enables parts to be manufactured layer by layer, which can result in the manufacture of extraordinarily complex geometries, topology-optimised designs, and lightweight lattice structures. The aerospace industry has greatly benefited more than any industry from AM's capabilities due to increased weight reduction requirements, high-performance materials, and an incentive to improve sustainability. However, there are still challenges because AM parts can have non-homogeneous material properties, defects created as the process runs, and distortion caused by unpredictable behaviour in machinery that are unfamiliar to aerospace component manufacturing, which limit the ability to produce 'end use' parts that are suitable for aerospace use. Smart monitoring, process automation, defect detection, and predictive maintenance have made AM more dependable and improved the quality of manufactured AM components. To overcome challenges of quality in AM, researchers have implemented the use of ML algorithms for monitoring the process, predicting defects, and optimising purposes. Table 2 provides a summary of example work using ML methods for quality control in AM.

Table 2: Applications of ML in AM Quality Control

ML Technique	Application Area	Key Contribution	Reference
CNN	Defect detection in L-PBF	Automated identification of lack-of-fusion and porosity defects using image/sensor data	[56]
LSTM	Procedure monitoring in aerospace engines	Prediction and mitigation of excess vibrations via time-series analysis	[57]
Support Vector Machines (SVMs)	Surface quality prediction in FDM	Classification of surface roughness based on process parameters	[58]
Random Forest (RF)	Thermal signature analysis	Correlating temperature fluctuations with defect formation in AM builds	[59]
Deep Belief Networks (DBNs)	Defect diagnosis in aerospace fuel systems	Improved fault detection accuracy and stability	[60]
Reinforcement Learning (RL)	Adaptive parameter control in AM	Dynamic adjustment of laser power and scan speed to minimise porosity	[61]

3. A Review of ML Approaches in Additive Manufacturing Quality Assurance

3.1 Inspection and Validation of AM Parts

AM components typically have geometries that are complex in nature, with inconsistent material properties. As such, quality assurance is a challenge, especially in aerospace applications where safety and reliability are paramount. Traditional inspection techniques also require a lot of time, which is why AI approaches are being examined. Research literature indicates that ML algorithms may be employed for surface structure metrology, porosity analysis, and dimensional variation identification. For example, a composite surface metrology algorithm that incorporates ML with multi-sensing data fusion to exactly characterise the surfaces of AM parts and ultimately showed improved accuracy in detecting defects compared with traditional inspection using a single sensor [62,63]. An augmented layer-wise spatiotemporal log Gaussian Cox process (ALS-LGCP) approach for binder jetting processes to quantify porosity distribution within layers.

3.2 Defect Detection in Powder-Bed Fusion Processes

The most significant additive manufacturing (AM) process for aerospace use is L-PBF. However, quality L-PBF parts are extremely sensitive to the amount of laser energy provided, the melt pool behaviour, and how the melt will cool. Ortmann et al. [65] explained the potential for an autonomous deep learning approach to assess melt pools via cross-sectional images of L-PBF parts. Their approach used segmentation networks to identify melt pool boundaries and measure dimensions throughout full sample cross-sections. This method enabled the identification of remelted areas and the evaluation of process instabilities. Significantly, their approach allowed the inference of the trend values across the build direction and enabled feedback on the variation of energy for the process, in near real-time.

3.3 Prediction of Geometric Distortion

Geometric distortion continues to be one of the most important challenges for AM parts in achieving aerospace tolerance standards. Moradi et al. [66] established an innovative deep learning framework, “CAMP-BD (Convolutional and Artificial Neural Network for Additive Manufacturing Prediction using Big Data)”, which integrated: CNNs for thermal imaging, to assess and extract local features of heat transfer; and ANNs to evaluate process limits. The outputs of the CNNs and ANNs were smoothed and concatenated to accurately predict potential pointwise distortions that even respected aerospace tolerance limits. This was an important progression for modern and data-driven distortion predictions, which will decrease costly trial and error in AM qualification.

4. Wire Arc Additive Manufacturing (WAAM) and ML Applications

4.1 Relevance of WAAM in Aerospace

The WAAM method is becoming increasingly popular in aerospace as it can produce larger parts, e.g., wing ribs, stiffened panels, or fuselage, etc. WAAM uses established welding techniques to deposit wire material at deposition rates of 50–130 g/min, which is noticeably faster than the laser-based processes, which deposit at rates of 2–10 g/min. To determine the important WAAM process parameters include layer roughness, weld bead width, depth of penetration, and bonding quality. Surface roughness is incredibly important because it has a considerable influence on machining costs, peak fatigue strength, and inter-layer adhesion. To model these traits and maximise WAAM process utility, researchers employed the algorithms RF and MLP. The results indicated that RF and MLP were able to adequately predict surface roughness with the application of different deposition strategies (straight path versus weaving path). However, RF superseded MLP both in accuracy of prediction and computational efficiency, demonstrating again the value of ensemble learning approaches such as RF for a valid and efficient plausibility of nonlinear process-property relationships in AM.

Fig.6 shows the three common arc-based processes used in welding and additive manufacturing with wire feeding. For “Gas Metal Arc Welding (GMAW),” a continuously fed electrode wire forms an arc with the workpiece under DC power and shielding gas. The shielding gas shields the molten pool from the atmosphere. In Gas Tungsten Arc Welding (GTAW/TIG with wire feeding), the tungsten electrode is sufficient to sustain the arc while also supplying external wire into the weld pool. The shielding gas surrounds the arc to provide more stable conditions and better quality welds compared to GMAW, while also providing higher energy input. Plasma Arc Welding (PAW) uses a similar arc process where the arc is constricted (focused) using the tungsten electrode and plasma gas to form a high-energy plasma jet to increase penetration and control. All three process styles (GMAW, GTAW, and PAW) provide indications of how the influence of electrode configuration, shielding gas, and arc plasma control are methods to stabilise the melt pool as a process for either joining material or fabrication by additive layer.

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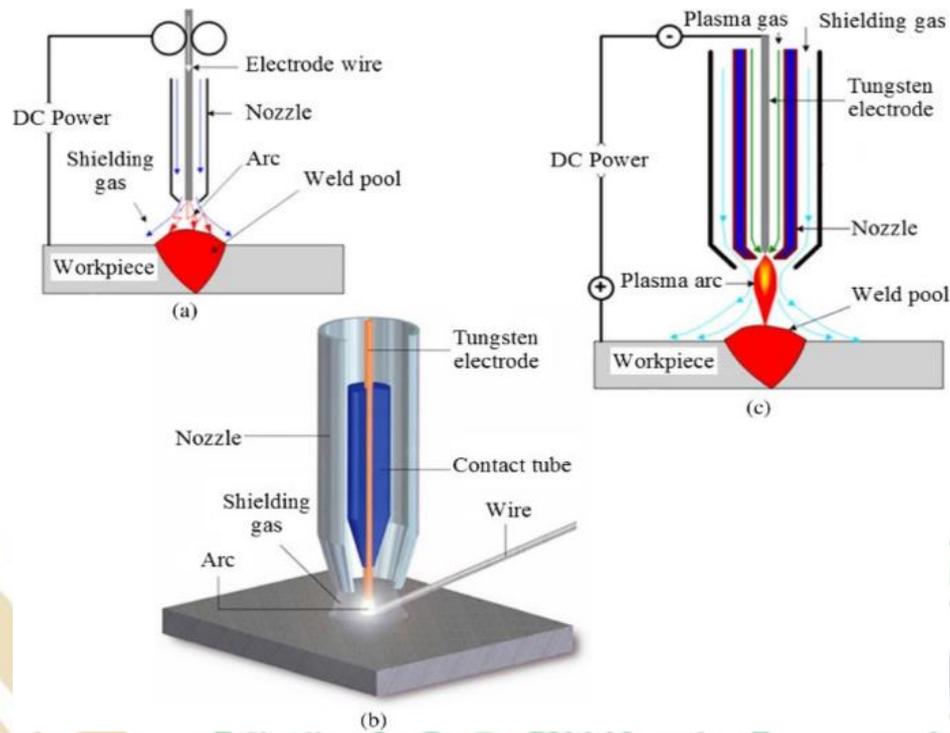


Fig. 6: Schematic Representations of Arc-Based Welding and Additive Manufacturing Techniques [67]

The applications of deep learning (DL) in aerospace additive manufacturing and maintenance are summarised in Table 3. Using DL methods supports generative design and topology optimisation in Design for AM (DfAM), while in-process monitoring is advancing real-time defect detection of pores, cracks, or melt pool instabilities. In the area of aircraft, DL dramatically improves predictive ability, applying to repair time estimations and identifying areas that are more prone to failures as compared to traditional statistical modelling. The future outlook also noted that adaptive process control and predictive laser-based manufacturing (LM) process techniques are expected to increase system uptime, efficiency, and safety margins for a range of aerospace applications.

Table 3: Applications of Deep Learning in the Aerospace Industry [68]

Domain	Deep Learning Applications
DfAM (Design for AM)	Generative design and topology optimisation to create lightweight, high-performance structures
Process Monitoring	Real-time defect detection (pores, cracks, unusual melt pool behaviour)
Aircraft Maintenance	Predictive maintenance, improved repair timeline forecasting, and failure-prone area detection
Future Outlook	Consolidation of process data for adaptive process control, predictive LM process techniques, increased machine uptime, and safety margins

5. Big Data Analytics (BDA) and Advanced Manufacturing (AM)

5.1 The Role of BDA in AM Processes

Additive manufacturing (AM) generates a substantial amount of data, comprised of sensor data, in situ data, thermal imaging data, and process data logs [69]. The volume of data generated requires a more sophisticated data mechanism than statistical tools can provide, prompting researchers and

practitioners to adopt Big Data Analytics (BDA) in AM. The BDA approach allows for: descriptive analytics, to visualise the state of an AM process; diagnostic analytics, to discover sources of process instability or root cause; predictive analytics, to predict part quality or machine health, based on historical data; prescriptive analytics, to recommend parameters that ultimately minimise defects or costs.

In additive manufacturing (AM), Big Data Analytics (BDA) significantly contributes to achieving improved efficiency of the processes, quality of the part, and reliability of the system in (Table 4). Descriptive analytics is used to illustrate the current state of AM processes and display how parameters, including melt pool temperature, layer quality, and energy input profiles, are trending to allow monitoring and improved process understanding in the current state. Diagnostic analytics provides additional insights by identifying the root cause of defects or instabilities during and after the printing process (i.e., porosity formation, distortions in layering, nozzle clogging), providing manufacturers with the necessary information to mitigate issues. Predictive analytics makes predictions based on historical and current conditions to anticipate future performance of outcomes (i.e., residual stresses, surface roughness, remaining useful life of components), and assist manufacturers in taking preventative measures to address significant issues without oversubscribing resources. Finally, prescriptive analytics depicts the most optimised parameters of the process that can minimise defects and costs through modifiable adaptive tuning to suitably update laser power, part scanning speed, or cooling rates. Taken altogether, these analytics will provide a comprehensive architecture to assist in monitoring, analysis, forecasting, and optimisation of AM processes to produce fewer defects and more efficiently.

Table 4: Applications of Big Data Analytics (BDA) in Additive Manufacturing (AM) Processes [70]

BDA Category	Purpose in AM	Example Applications
Descriptive Analytics	Visualises the current state of AM processes	Real-time dashboards of melt pool temperature, layer quality, and energy input profiles
Diagnostic Analytics	Identifies sources of process instability or root causes of defects	Analysis of porosity formation, distortion patterns, and nozzle clogging issues
Predictive Analytics	Forecasts part quality, machine health, and process outcomes using historical data	Predicting residual stresses, surface roughness, or remaining useful life of components
Prescriptive Analytics	Recommends optimised process parameters to minimise defects and cost	Adaptive parameter tuning (laser power, scan speed, cooling rates) for defect reduction

5.2 BDA + IoT for Smart AM

By integrating BDA with the IoT, manufacturers can now view the AM process in real time. Sensors enabled by IoT technologies will capture and create a deluge of data about temperature, vibration, power consumption, and material flow on an AM machine that can be organised inside BDA pipelines. To develop smart additive manufacturing ecosystems by leveraging AM, BDA, and IoT capabilities, by improving product quality, minimising waste, increasing machine uptime, and improving predictive maintenance. Bi et al. also indicated that cloud computing and cybersecurity would assist with preserving data integrity and accessibility within a smart AM factory.

6. Sustainable Smart Additive Manufacturing (SSAM)

The next direction in AM's advancement is the joining of sustainability concepts with smart manufacturing. Han et al. [71] presented a Big Data-driven Sustainable and Smart Additive Manufacturing (BD-SSAM) framework, which is particularly relevant to the aerospace and automotive sectors. Their framework employed Big Data Analytics (BDA) algorithms in the Selective Laser Melting (SLM) of AlSi10Mg alloys for optimising process parameters to minimise energy consumption, while still producing to elevated levels of acceptable quality standards. While the framework focused mainly on the Beginning of Life (BoL) stage of the product lifecycle, results suggested that energy efficiency and dimensional accuracy improved significantly. Further research on BD-SSAM should be done in the future as consideration is given to the entire product lifecycle, particularly for End of Life (EoL) recycling and reusability of materials.

Fig. 7 provides an idea for an Additive/Subtractive Hybrid Manufacturing (HASM) system, which uses both additive and subtractive processes in one manufacturing workflow. On the left, the study can see the additive process, which involves a material (such as a metallic wire or metallic powder) being deposited in layers using a plasma head assisted with a laser to create the desired geometry, as seen in this example. The plasma plume and deposited layers demonstrate how melting and resolidifying occur at localised sites in additive manufacturing. On the right, the study can see the subtractive process, where a cutter mills or removes excess material in the deposited layers to obtain dimensional accuracy and smooth surface finish. Hence, a HASM system allows for the production of complex, high-precision geometries while minimising waste of the material and improving the surface finish of the part. A HASM approach is desirable in aerospace and high-performance applications where complex geometries, mechanical properties, and dimensional tolerances are crucial.

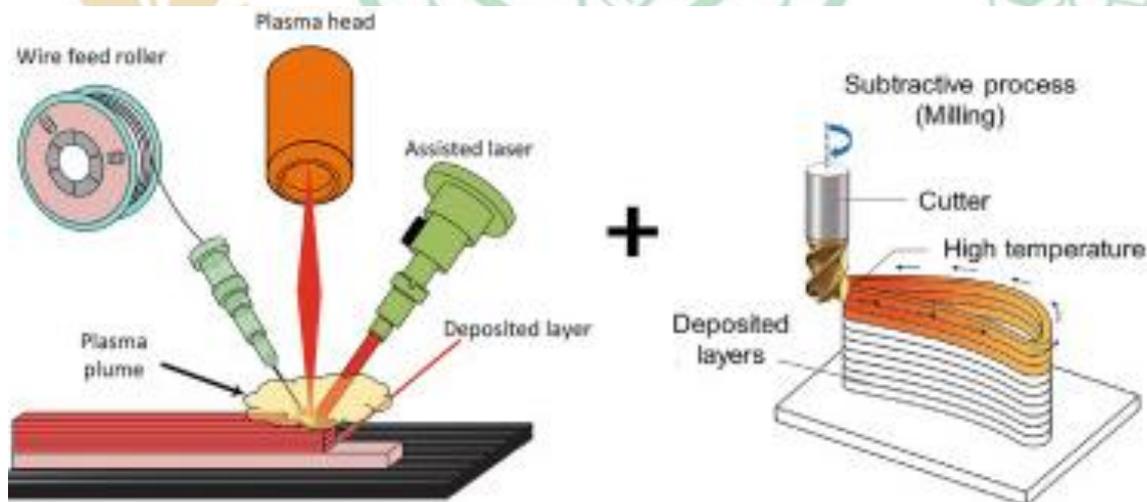


Fig. 7: Additive/ Subtractive Hybrid Manufacturing [72]

AM systems by reviewing AI-enabled applications concerning product design, process control, and service delivery. Their review identified specific gaps in research relating to algorithm interpretability, multi-objective optimisation, and real-time decision-making. Moreover, emphasized that “Industry 4.0 technologies” support more efficient, effective, and customer-responsive AM processes [73]. Additionally, an MCDM technique using the AHP to rank Industry 4.0 drivers for AM [74,75]. Their findings revealed that cloud-integrated AM platforms and high-throughput AM systems were the "most prevalent" enablers for the near future. The adoption of technologies as applied to AM workflows can improve the aerospace sector's capability to produce dependable, lightweight, and sustainable components. AI-based strategies are already addressing shortcomings in conventional AM processes—from defect detection to predicting porosity, creating distortion models, and optimising surface roughness. Frameworks such as BD-SSAM, combined with cloud computing solutions and

Industry 4.0, will hasten the shift toward Sustainable Smart Additive Manufacturing (SSAM). Much progress has been made, but challenges remain, specifically for real-time defect control, optimisation for the lifecycle of the products, and AI model interpretability. Future research is needed to consider multi-scale modelling of AM, hybrid AM technologies, and the enablement of closed-loop feedback control to develop fully autonomous, sustainable manufacturing of aerospace components.

7. Design For Additive Manufacturing (DAFM)

Optimising the design leads to reduced material use, resulting in lower consumption of raw resources. In addition to reducing material use, optimised design also positively affects aircraft performance and reduces the energy and transport costs of manufactured items. Additive manufacturing methods have permeated many engineering disciplines due in part to being able to reduce weight, and because of their rapid prototyping capabilities [76, 77]. The design strategy that studies the geometry of an object is considered among the best strategies in aerospace engineering to reduce weight and performance. Generative design enhances traditional engineering practices by giving engineers more potential to meet a variety of priorities for design (lighter parts, lower costs, stiffer parts, etc.) and material efficiency. The next sections will take a closer look at topology optimisation and generative design procedures, focusing on how design provides weight savings while delivering manufactured engineering products at a higher standard of quality.

The approach presented in Figure 8 shows a DfAM-based framework for alloy development, incorporating materials designed specifically for the operability of metal AM. The workflow begins by identifying application performance needs, followed by the selection of alloy chemistry best suited for the cooling rates and thermal gradients of AM processes, and PBF is identified as one of the two main AM routes to manufacture, test, and validate the alloys being developed. This demonstrates a shift in alloys development approaches to one driven by DfAM, and where the material, process, and design are developed in tandem. The framework outlined in the figure assists in reinforcing the notion that AM is neither primarily a shaping technology nor a process by which materials are manufactured, but rather a method for producing materials, with faster and more effective process opportunities to generate pre-service design. AM, within the framework of DfAM, enhances the opportunity for the manufacture of advanced materials, including high-entropy alloys, aluminium, titanium, steel alloys, and magnetic alloys, which can be engineered to perform at a higher level when designed with AM in mind.

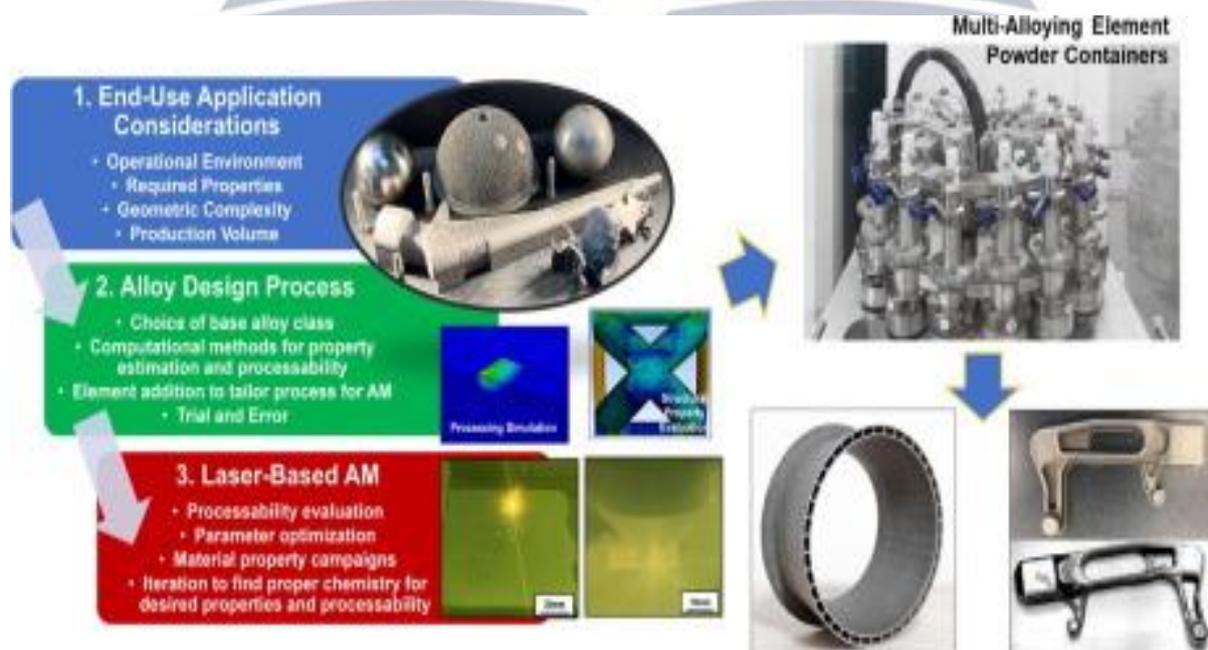


Fig 8: DfAM-Based Workflow for alloy Development [78]

7.1 Topology Optimisation

Topology optimisation (TO) is a crucial tool in the aerospace industry for generating lightweight and creatively efficient components. It is frequently employed in designing airframe configurations, panel-stiffeners, multi-component systems, and fastener assemblies. TO helps organise material within the design space regarding mass and stiffness for optimal structural performance, while also reducing weight [79]. The emergence of AM has elevated the role of TO in aerospace, as composite TO with AM can support reduced structures, reduced manufacturing time, and eliminate waste for parts and materials, which can, in turn, lead to efficient, high-performance, cost-effective, and environmentally-friendly aerospace components. Several studies have established a variety of practical advantages obtainable by combining TO with AM. For instance, Xian et al. [80] demonstrated an approximate reduction of 40% in lifecycle CO₂ emissions, which was achieved through the use of optimised geometry and weight reduction to achieve a functional metal part (direct metal laser sintering) designed by a TO process (Airbus A320 nacelle hinge bracket).

Shi et al. utilised thermo-elastic topology optimisation (TO) to create brackets that considered both mechanical and thermal loading to create lightweight and strong components with selective laser melting (SLM). Similarly, Trudel et al. proposed a multi-tier optimisation framework that integrated topology, shape, and size optimisation for additive-manufactured lattice-based structures for aerospace applications, concluding a weight reduction of up to 44% while achieving comparable structural performance. Hybrid additive–subtractive manufacturing (HASM) methods broaden options and take advantage of the geometrical freedom related to additive manufacturing (AM) while providing the dimensional accuracy of subtractive manufacturing. More advanced methods, such as bi-directional evolutionary structural optimisation (BESO), also include constraints on manufacturing to help with TO approaches; however, problems with thermal stresses, residual strain, and surface finish remain in AM materials. TO, by leveraging the benefits of AM and HASM, can achieve mass savings ranging from 18% to over 60% while resulting in comparable or more reliable structural performance. Research into TO in air and space applications is also looking at multiscale optimisation, multifunctional designs, functionally graded materials, and better manufacturing-friendly algorithms [81]. As a result, next-generation aerospace structures for air and space will need to be lightweight, performable, and priced better to lower costs to the consumer.

The table illustrates how topology optimisation (TO) is applied and the overall benefits for aerospace of TO, especially when viewed through the lens of AM and hybrid additive–subtractive manufacturing (HASM) [82]. The component design row shows how TO provides a means of organising material in a rational way that efficiently reduces weight without compromising overall structural integrity, represented by the example of the Airbus A320 hinge bracket, which reduced lifecycle CO₂ emissions by 40%. Thermo-mechanical optimisation relates to the design of a component that considers mechanical loads and thermal effects, thereby ensuring the functionality of a part is lightweight yet remains strong in operational conditions, as illustrated by the example of brackets produced with selective laser melting (SLM). The multi-tier optimisation approach is also shown, incorporating topology optimisation, shape optimisation, and size optimisation to optimise the structures, represented by the door hinge produced with a lattice material that minimised weight and stress concentration around hinge points [83]. The hybrid manufacturing (HASM) row makes clear the ability to utilise what AM offers in terms of geometric opportunities and combine this with a subtractive machining option to provide accuracy, improve surface finish, and reduce residual stresses. Performance enhancements encapsulate all of the advantages of topology optimisation (TO) and additive manufacturing (AM), resulting in lightweight, multifunctional, and environmentally sustainable components with mass reductions of 18% to over 60% and little or no decrease in structural reliability. Lastly, the challenges row addresses familiar problems, such as structural support optimisation, thermal management, multi-material design, and machining complexities. Table 5 conveys that TO and AM together can optimise aerospace components for weight, performance, and sustainability,

while also delineating the additional research needed in identified areas.

Table 5: Applications and Benefits of Topology Optimisation in Aerospace [84]

Aspect	Description / Application	Example / Outcome
Component Design	Systematic material distribution for weight reduction	Airbus A320 hinge bracket – 40% CO ₂ reduction (Meng et al.)
Thermo-Mechanical Optimisation	Designs considering mechanical and thermal loads	Aerospace bracket with SLM, maintaining strength and thermal performance (Shi et al.)
Multi-Tier Optimisation	Integration of topology, shape, and size optimisation	Aircraft door hinge lattice – 44% weight reduction (Trudel et al.)
Hybrid Manufacturing (HASM)	Combines AM freedom with subtractive machining accuracy	Improved surface finish, reduced residual stresses (Han et al.)
Performance Improvements	Lightweight, multifunctional, environmentally sustainable components	Weight reduction 18–60%, reliable structural performance
Challenges	Support structure optimisation, thermal stresses, multi-material design, and machining complexity	Requires advanced algorithms and material studies for AM/HASM

7.2 Generative Design

Further, it is suggested to focus on developing topology optimisation for more advanced methods used in creating multifunctional and monolithic products. Also, more research is needed in multiscale topology optimisation, particularly when optimising the macrostructure while considering the local material properties at the microstructure level. Jihong and colleagues [85] reviewed existing literature on integrating with AM. The findings show that combining structure, material, process, and performance is key to achieving high-performance, multi-functional, and lightweight manufacturing. The literature clearly shows that topology optimisation helps designers explore a wider range of design possibilities through a freeform material distribution approach, allowing for more creative structural designs [86-88]. During the structural development, designers can create, combine, and separate different internal solid and hollow regions. After additive manufacturing, parts often need some subtractive machining to achieve a better surface finish and precise dimensions. However, using topology optimisation for AM components can limit the possibility of post-machining, as it results in complex geometries that are costly to machine [89-91]. Therefore, there is an opportunity to create a more cost-effective and machining-friendly topology design for AM parts, which can be achieved by developing smart design algorithms. There is considerable research on how topology optimisation aligns with material and manufacturing uncertainties, as well as geometric nonlinearities. Additionally, there are many studies on topology optimisation for functionally graded and multi-material parts. However, there is still a need to explore the complexity of interface distribution, grain size, and porosity in metal AM processes. From the existing studies, it is evident that integrating topology optimisation with additive manufacturing has a major impact on modern manufacturing. Nonetheless, the field of structural optimisation remains a key area of interest and requires further investigation, especially when combined with functionally graded materials.

7.3 Modelling

Metal additive manufacturing (AM) has gained significant interest in aerospace for producing lightweight, high-performance components. However, the “layer-by-layer” process introduces challenges such as complex microstructures, residual stresses, distortion, and thermal gradients, which can impact mechanical properties and dimensional accuracy. Modelling and simulation have become essential tools for understanding and predicting these effects, linking process parameters to material performance [92-95]. Simulation approaches in AM can be categorised as analytical, empirical, and numerical. Analytical models offer simplified predictions but are limited for complex geometries. Empirical models rely on experimental data to predict trends, while numerical methods, including FEA and CFD, provide detailed multiphysics simulations of thermal, mechanical, and microstructural behaviour. Studies demonstrate the role of simulations in process optimisation. For example, thermoelastic stress modelling in electron beam melting (EBM) for titanium alloys highlights residual stress challenges [96-98]. In wire arc AM (WAAM), simulations show that heat distribution and welding speed significantly influence thermal stresses and plastic strains. Laser-based processes, such as SLM and L-PBF, have been extensively modelled to optimize laser power, scan speed, layer thickness, and heat-affected zones, balancing porosity, mechanical properties, and distortion. Direct energy deposition (DED) modelling focuses on surface finish and layer uniformity. Despite advances, electron beam-based methods remain less explored due to their unique thermal environments. Overall, modelling and simulation enable the prediction of microstructure evolution, residual stress formation, and mechanical performance, allowing aerospace engineers to optimize process parameters, reduce defects, and improve component reliability while minimizing experimental costs [99].

Table 10 categorizes the dominant modelling methodologies applied to metal AM (additive manufacturing) for aerospace purposes and lists their targeted applications and relevance. The analytical models provide simplified mathematical representations of thermal and mechanical behaviour occurring during the AM process. Analytical models are appropriate for understanding, conceptually, one-dimensional heat transfer or stress response results, but can be limited in accuracy, with complex geometries or multi-physics effects. Empirical models are rooted in experimental observation and collected datasets to trend residual stresses, microstructure evolution, and dimensional accuracy [100]. Empirical models are important models, especially for process-specific knowledge, but are highly dependent on experimental data, and the supporting data must be accurate. Numerical simulation is the most prevalent class of materials modelling, which includes FEA and CFD. These modelling methods facilitate a detailed multiphysics modelling of heat transfer, solidification, residual stress work, distortion, and microstructural evolution, for example. Numerical simulations have been leveraged to forecast performance in processes such as proven L-PBF, EBM, and wire arc additive manufacturing (WAAM), in which simulation outcomes support the optimization of process parameters in laser power, scan speed, and powder feed rates. Collectively, these modelling approaches present ways for engineers to account for the performance of aerospace structures, to limit defects, and to create reliable parts that can be produced as parts that are lightweight, high-performance, and safe for aerospace applications [101].

Table 10: Modelling Approaches and Applications in Metal AM for Aerospace [102]

Model Type	Description	Applications / Outcomes
Analytical	Mathematical representation of 1D thermal or mechanical behaviour	Quick estimation of thermal response; limited to complex geometries
Empirical	Based on experimental observations	Trend analysis for process parameters, dependent on available data

Numerical (FEA/CFD)	Detailed multiphysics simulations including heat transfer, stress, and microstructure evolution	Predicts residual stress, distortion, melt pool behaviour, layer deformation; used in SLM, L-PBF, WAAM, DED, EBM
Thermoelastic Models	Coupled thermal-mechanical simulations	Residual stress prediction for titanium alloys and WAAM components
Mesoscale Models	Time-adaptive simulations of cooling and solidification	Microstructure evolution, stress accumulation, and deformation prediction
Optimization Studies	Process parameter tuning via simulation	Improved mechanical properties, reduced porosity, controlled distortion, better surface finish

The different modelling domains of Additive Manufacturing are illustrated in Figure 6. These domains will often include, but are not limited to thermal modelling, to simulate temperature distribution and cooling rates; mechanical modelling, to predict residual stresses and distortion; and microstructure modelling to gain insights into the formation of grains and phase changes during the solidification of material. Oftentimes, powder flow and laser-material interaction modelling are also utilized to simulate the behaviour of the material before and during the melting process. In sum, the different modelling domains can all provide the researcher/engineer with predictive capability of the AM process, enabling control of and/or reducing variations in the final part properties, minimizing the amount of trial-and-error in the AM process, and improving processes to support the development of new materials and geometries with unique properties to the AM process and device. Figure 6 conveys how the different modelling domains can develop a digital bridge to optimize and provide quality assurance for AM technologies.

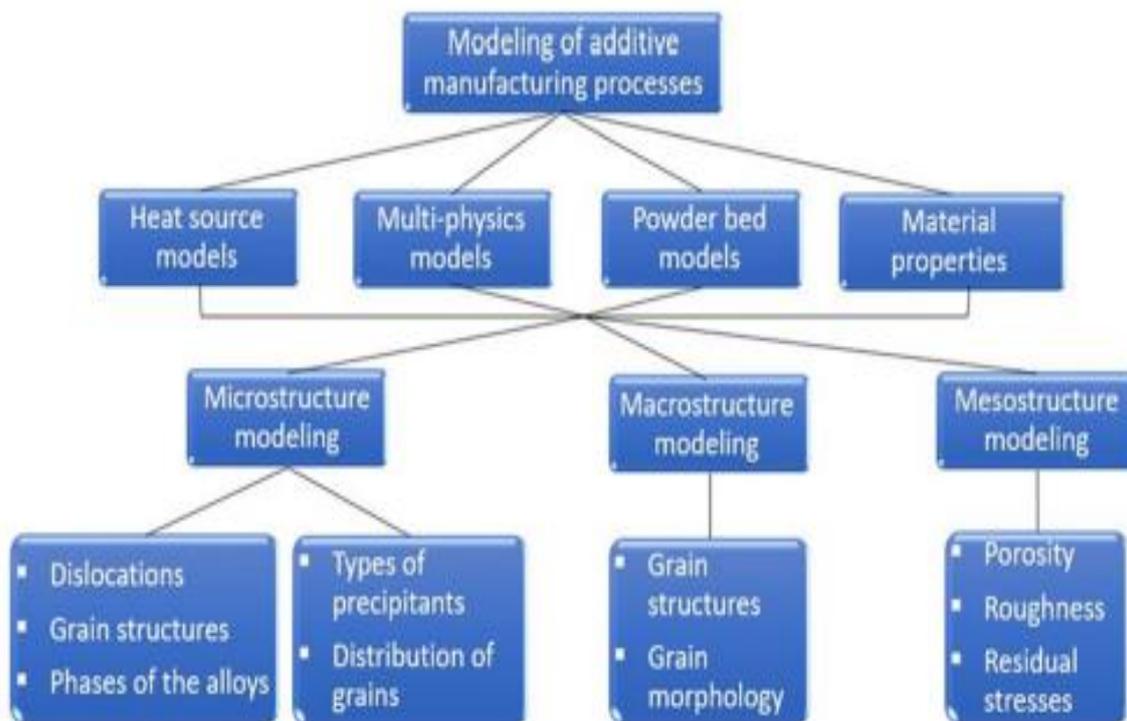


Fig. 9: Different extents of modelling of AM processes [103]

8. Challenges and Scope

Additive manufacturing (AM) technologies have shown enormous potential in reducing mass, improving design options, increasing fuel efficiency, and speeding up manufacturing in aerospace applications. However, there is still a major gap in understanding how to apply these technologies effectively in commercial aviation [104, 105]. Issues like mismatched material properties and dimensions, as well as surface finish problems, are still a concern. AM is likely feasible for speciality steels, titanium alloys, ceramics, and nickel alloys. There is a strong need for a baseline database of material characteristics for AM materials to support the industry. Physics-based models are also needed to predict material properties, such as strength and fatigue resistance, before they are used, especially since these materials may be exposed to extreme conditions. Metal 3D printing technology is already available on the market. Cloud computing also offers opportunities, as it can help process large datasets more quickly and affordably [106]. For AM to become the preferred method for real-world applications, key challenges must be addressed, such as anisotropic mechanical properties, overhanging structures, prohibitive costs, slow production rates, warping, and the limited range of available materials [107]. Aerospace components face various stresses during their service life, including corrosion, sudden impacts, thermal changes, and fatigue. These factors can cause defects, warping, cracks, and failures. As a result, repair and remanufacturing are used to restore components to working condition. Directed energy deposition (DED) is widely used in these repair and remanufacturing processes due to its high precision, less distortion, narrower melting zones, and smaller heat-affected zones. Several research teams have conducted studies on repairing and remanufacturing damaged aerospace parts using DED [108–111]. BAAM (Big Area Additive Manufacturing) is transforming how large components are made for various applications around the world. It has opened new opportunities for mechanical testing and manufacturing. BAAM can produce large parts in a single print, offering cost benefits by eliminating the need for heavy investments and long lead times typically required for traditional manufacturing. However, BAAM is still an emerging technology that requires further development to fully address manufacturing challenges while producing even larger components.

9. Conclusion

AM has become a reliable platform to meet the increasing demand for making complex, multi-material, and highly detailed parts in the aerospace industry. During the manufacturing process, AM generates a lot of data that needs to be collected, analysed, and used to improve performance and reduce costs. By combining AM with AI, the Internet of Things, big data analytics, process simulation models, and cloud technologies, the reliability of the products can be enhanced. This study thoroughly reviewed existing literature on AM processes used in aerospace, focusing on machine learning and deep learning methods, large-scale additive manufacturing, topology optimisation, generative design, knowledge-based process planning, big data analytics, the Internet of Things, and process simulation modelling for aerospace components. The study also highlighted challenges and future opportunities to improve algorithm-driven “AM processes” for designing and manufacturing aerospace parts. The conclusions drawn from this review are as follows. ML methods are extensively employed in the additive manufacturing (AM) process of aerospace components, with the expectation of lower costs, shorter lead times, reduced weight, improved energy efficiency, etc. These methods will reduce the time it takes to bring a product to market (product development cycle) for aerospace components.

The DL models, deep autoencoders, long short-term memory, and convolutional neural networks, deep belief, and some of their hybrid structures are mainly used for diagnosis, anomaly detection, and prognosis in vertical areas of the aircraft. Studies revealed that DL often outperforms model-based and statistical ML models. However, few studies use DL in the AM of aerospace components. “Large-scale additive manufacturing (LSAM)” is being recognised as a cost- and time-efficient process method for producing large components. However, LSAM requires the investigation and resolution of

some issues associated with the production of large parts. “Hybrid additive-subtractive manufacturing (HASM)” is becoming more common, and yet few studies have attempted topological optimisation for HASM. More research is needed on constraints for HASM, including residual stress/strain with thermal stress, production defects, and inter-layer fusion. Advanced topological optimisation algorithms for multifunctional and monolithic products are also needed. GD for AM has created “light-weighting possibilities, increasing performance and functions of parts while ensuring that the right design is delivered to the right manufacturing technology.” GD software has advanced to the point that engineers can optimise aerospace designs to increase engine efficiency, reduce drag, and reduce mass in order to reduce the life-cycle cost of the plane. Integrating AM and IoT offers high product quality, reduced production scrap, improved process analysis and feedback, and lower setup costs, errors, and downtime. Modelling and simulation of AM provides an understanding of microstructure and residual stresses with respect to processing parameters. There has been a lot of work done on modelling the dynamics of the selective laser melting (SLM) process with respect to scan velocity, powder-layer thickness, scan spacing, and power. There are limited studies of the Electron Beam Melting (EBM) process.

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Abbreviation

Abbreviation	Full Form
ACO	Ant-colony Optimisation
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 Optimisation
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

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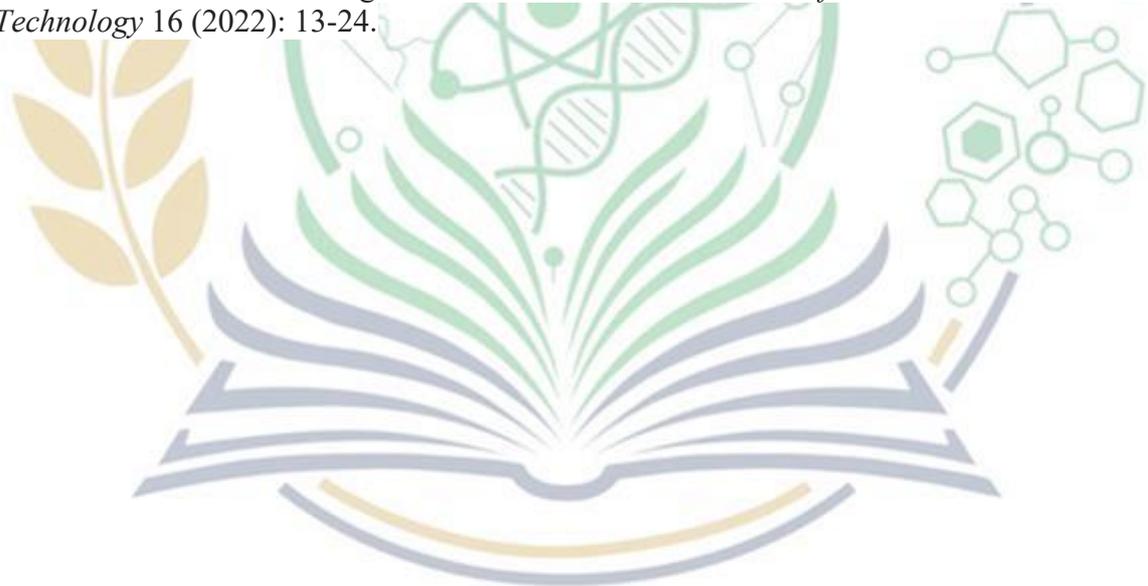
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