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Review

Design Optimization Method Based on Artificial Intelligence (Hybrid Method) for Repair and Restoration Using Additive Manufacturing Technology

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Abstract: The concept of repair and restoration using additive manufacturing (AM) is to build new metal layers on a broken part. It is beneficial for complex parts that are no longer available in the market. Optimization methods are used to solve product design problems to produce efficient and highly sustainable products. Design optimization can improve the design of parts to improve the efficiency of the repair and restoration process using additive manufacturing during the end-of-life (EoL) phase. In this paper, the objective is to review the strategies for remanufacturing and restoration of products during or at the EoL phase and facilitate the process using AM. Design optimization for remanufacturing is important to reduce repair and restoration time. This review paper focuses on the main challenges and constraints of AM for repair and restoration. Various AI techniques, including the hybrid method that can be integrated into the design of AM, are analyzed and presented. This paper highlights the research gap and provides recommendations for future research directions. In conclusion, the combination of artificial neural network (ANN) algorithms with genetic algorithms as a hybrid method is a key solution in solving limitations and is the future for repair and restoration using additive manufacturing.

Keywords: additive manufacturing; repair and restoration; design optimization; design for additive manufacturing; artificial intelligence; hybrid method

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1. Introduction

According to ASTM International, additive manufacturing (AM) technology can be defined as making an object by joining materials layer-by-layer from 3D model data [1]. In industrial fields, there are many systematic methods used for prolonging the life of components, tools, equipment, and devices. Conventional methods for repairing and restoring the durability of parts mainly rely on human decisions and skills. However, progress in manufacturing technology and automation in recent decades has led to repair and restoration using AM technology.

At present, the repair of tools and components is widely used to enhance the circular economy (CE). AM technology offers a good alternative for industry by saving repair and restoration time and avoiding material wastage while maintaining the same product durability. Prioritizing remanufacturing is an important aspect of achieving the circular economy with end-of-life (EoL) recovery and the reproduction of complex old products to the same original quality rather than being recycled [2].

CE is a transition and shift from the traditional principle of make–use–dispose to a new era based on artificial intelligence [3]. There are several strategies used for circular product design. The first strategy is to increase recycling performance, the second is to boost material performance, and the third is to expand the lifecycle of products [4]. Manual reparation and restoration are now replaced by automatic and digital processes, such as AM, where this process is capable of melting many material layers in one process [5]. Complex spare parts have a long lead time in the manufacture and production phases of suppliers and have high costs. Downtime due to the lack of spare parts availability means non-operation situations and stoppages. AM is the solution to reducing downtime, costs, the number of unused components, and waste. It is possible to create flexibility by locating AM systems near the operating units [6].

The advantages that lead to high demands for AM include creating complex geometries with good performance, customization, and lightweight products. Despite the advancement in manufacturing technology, advances in design for AM are still lacking, and more research is required [7]. This is important to improve the additive manufactured parts during the early stages of development [8]. AM and AI can be used together to utilize and combine knowledge toward intelligent physical network systems [9]. The exchange of the product database and knowledge between design engineers based on AI through the network is called collaborative design. It focuses on knowledge integration and big data sharing toward better resource management and innovation in the AM domain [10]. Many studies have explored the usefulness of artificial intelligence (AI) in additive manufacturing and have concluded that AI-enabled additive manufacturing results in significant cost reductions. Many researchers have investigated the applicability of AI in additive manufacturing. Literature studies show that researchers have proposed the implementation of AI for speeding up prefabrication in 3D printing [11]. The involvement of AI in remanufacturing using additive manufacturing increases the efficiency of the remanufacturing process. This includes component design optimization to facilitate the repair and restoration process using AM and will help to ease the burden on designers and manufacturers to analyze the types of failures prior to the restoration process.

Hybrid additive manufacturing, also known as hybrid manufacturing, is a combination of additive manufacturing processes, such as directed energy deposition (DED), and conventional manufacturing processes, e.g., computer numerical control (CNC) milling. Hybrid manufacturing requires determining the sequencing process between subtractive and additive, generating process planning alternatives, and inspection operations. Building a part from scratch or the repair of a component is considered the starting point. Alternatives can be generated depending on the combination of subtractive, additive, and inspection based on the combination of additive, subtractive, and inspection operations [12]. For further optimization, specific hybrid algorithms, such as the particle swarm optimization (PSO) algorithm, and the evolutionary optimization, artificial neural network (ANN), and genetic algorithm (GA) methods, can be adopted to improve additive manufacturing processes [13].

This review paper identifies and highlights product lifecycle from different points of view, including remanufacturing, design, optimization, applications, and the relationship with AI. It also aims to highlight the benefits and application of artificial intelligence (AI) in AM. It presents the latest trends in this research. Moreover, it involves many analyses and evaluations regarding the methods of restoration using AM technology and how to work with AI techniques to make them more useful and efficient. It also focuses on the methods of design optimization of this restoration process by adopting the AI technique, including using the hybrid method. It also explores and identifies all the means and possibilities that lead to maximum benefits of design optimization-based AI in AM applications by analyzing previous research in this field. The final findings of this review should answer whether hybrid AI is the best application to enhance design optimization for the additive manufacturing process [14].

2. Background on Additive Manufacturing

AM is an advanced method for the repair and restoration of EoL components of complex geometries by adding material layer-by-layer. Compared with the manufacturing of a new product, remanufacturing is considered a good strategy for recovering the deformed and broken components and saves material, time, and energy. In addition, to saving cost and time, the other main reasons for restoring components by AM in the end-of-life stages are environmental. Facilitating the rescue of recyclable components is one of the important objectives in designing products for AM [2]. The idea of integrating remanufacturing and AM processes is highly recommended for overcoming technological restrictions and for improving the quality of restored components.

Three-dimensional parts can be built effectively using AM process by adding thin material layers to the intended model. Complex parts are directly produced in a few processing steps and without the need for new extra tooling such as casting molds [1,15]. AM technology is accepted as a good alternative for reproducing some complex components for many reasons, such as decreasing the inventory, producing on-demand parts, and having high efficiency [16]. The potential influence of AM on improving engineering functionality and material performance is great. AM has a large impact on the aircraft industry as the adoption of AM in the manufacture of components has many advantages in terms of cost and optimum, lightweight design. A shift to AM technology reduces greenhouse gas emissions and creates energy savings in the aircraft industry [17].

This promising method reveals many additional benefits which cannot be implemented through the AM method, including the possibility of designing complex geometries and reducing the environmental effects by avoiding scrap jams [17]. In addition, the adoption of the AM process in the manufacturing of specific components will lead to a reduction in overall weight and the enhancement of aircraft efficiency. The capabilities and principles of AM technology presented for the restoration and rebuilding of complex components to extend their working life for the circular economy depend on many factors, including geometrical dimension, tolerances, complexity, and compatibility of the restored material [18]. Based on the ASTM Standard F2792 [14], there are seven classifications of AM processes, among these, two are suitable for remanufacturing, which are powder bed fusion (PBF) and directed energy deposition (DED). Most AM-fabricated metal components require postprocessing and heat treatment. DED AM processes and PBF AM processes are considered direct-to-metal AM processes while ultrasonic additive manufacturing is an example of an indirect AM process. There are some differences between the PBF and DED-based AM techniques, depending on the quality, product size, and overall costs. Based on high-energy heat sources and localized melt solidification, PBF AM and DED processes fall under the same category and share similar fundamentals [16].

The ultrasonic additive manufacturing (UAM) process uses ultrasonic vibrations for joining layers of metallic sheets. The feeding of raw materials depends on the type of AM process. A laser beam is used for coaxially feeding the alloy powder into the DEB process, while in PBF-based AM, to avoid defects such as poor mechanical properties and bad surface finish, solid powders are used. The characterization of AM processes depends on many factors such as dimensional accuracy, production times, size of the fabricated component, and the quality of the product. One of the important techniques used in AM for printing 3D objects is fused deposition modeling. This method is normally used with polymers by the deposition of successive layers to build the model layer-by-layer. Fused deposition modeling is a promising method in AM with a high impact on many modern applications by reducing costs and operation time [19]. Laser cladding and directed energy deposition are examples of advancements and development in repairing components using AM processes.

Among many AM techniques, electron beam melting (EBM), selective laser melting (SLM), and directed energy deposition (DED) are the most used in the restoration and repair of product defects. A comparison was made for the fabricated Ti6Al4V using AM methods and traditional manufacturing based on mechanical properties, microstructures, and processing parameters. In AM, the fatigue life of Ti6Al4V increases, and crack initiation weakens if there are post-heat treatments [20]. SEM test and analysis showed significant improvements in mechanical properties due to laminate formation in the AM process. It is found that the increase in the number of laminates will make the distribution of added material more uniform and reduce the possibility of void formation [21]. During the repair and restoration process, energy consumption depends on the main characteristics of the heat source. Gaussian profiles are used to calculate the distribution of power density on the surface, as in Equation (1) [16]:

$$P_d = \frac{f\ P}{\pi r_b^2} exp\left(-f\frac{r^2}{r_b^2}\right) \tag{1}$$

where P_d is the power density on the surface, f is the distribution factor, r is the radial distance of any point from the axis of the heat source, and r_b is the radius of the heat source. Since the powder particles are small in size, powder-based AM processes are suitable to produce smaller parts with good features, such as good strength, dimensional stability, and smooth surface finish, while high-weight components are produced using wire-based processes. AI can be used to enhance and make a good integration in AM restoration by supporting decision making and enhancing the repair performance during the remanufacturing process.

Challenges in Additive Manufacturing Process

The special characteristics of powder bed fusion-based additive manufacturing processes, such as SLM and EBM, are based on a layer-by-layer process to melt metal powders using a laser and electron beam, respectively. This brings its own challenges and limitations with regard to the mechanical properties of the parts produced. The temperature, scanning speed, and hatching distance influence the mechanical properties of the parts produced. Therefore, concerning repair and remanufacturing, optimized manufacturing parameters must be chosen to obtain the desired outcome. It is important to determine the most suitable temperature for the AM process since it strongly correlates to the quality properties of the part. Temperature parameters are also related to thermal conductivity and mass density. There are many challenges in AM processes, such as the physical properties of the material at elevated temperatures, the material geometry, and the properties of the raw material [22]. Hence it is important to control and monitor these parameters. Monitoring capabilities are becoming an important factor in the development of AM processes, as they enable quantifying and measuring the variables and detecting the process limitations. Moreover, the monitoring of process defects and limitations will enable the verification of process models. Each AM process has its specific limitations. For example, the beam interference solidification (BIS) process is associated with technical limitations, such as the shadowing effects from the insufficient absorption of laser radiation at higher depths and leading to difficulties in obtaining the precise intersection of the beams [22].

SLM and EBM, being a PBF-based process, also bring challenges in repair and restoration to the part geometry, with the addition of material only where required and obtaining the exact dimensions. For other AM processes, such as directed energy deposition (DED) and wire-arc additive manufacturing (WAAM), the process does not rely on a powder bed and therefore is more suitable for repair and restoration. In DED, a laser is directed toward the part where the heat source melts the metal powder or wire from above and deposits it onto the surface of the part. Hence it is easier to correctly position the part for the remanufacturing process.

Another important challenge in the AM process is related to carbon emissions [23]. Determining the carbon footprint of manufacturing processes and the environmental impact are important steps that need to be further optimized to make processes greener and more sustainable. Improvements in the AM process bring benefits toward carbon neutrality and further improvements can be achieved [24].

3. Artificial Intelligence Applications in Additive Manufacturing Technology

The most common definition of AI (artificial intelligence) is that science deals with building programs for computer numerical machines to react and perform tasks like humans [25]. It is the science of making computerized machines intelligent and thinking and making a decision similar to humans through using some programming methods. AI is a very sophisticated and powerful knowledge used in many planning and operation systems with a great ability to deal with, manage, and respond rapidly in the minimizing and solving of mathematical complexity. Mathematical optimization and comprehensive analysis were implemented for solving the problem of designing power system stabilizers by using different types of AI techniques [26]. Nowadays, AI is used by developers and product designers as a great option for building many prototypes with multiple versions at the same time to increase productivity and quality [27]. These smart technologies, such as the Internet of Things (IoT) and AI, are good enablers for the circular economy by accelerating information sharing between customers and companies through website applications [28]. The rapid development of high-technology equipment results in utilizing this evolution for enchasing and optimizing AM processes based on new concepts built on knowledge and high-accuracy communication networks with technologies called the internet of things (IoT) [28,29].

Prediction, diagnosis, and detection of damages and failures is the main purpose of the use of AI in manufacturing applications. The ability to assist in the design and optimization of different types of parts failures is another benefit to human knowledge related to many fields of science such as design procedure, material science, and repair processes, which are significantly required in intelligent system development. Better human replication in decision making, thinking, and the ability to attain design optimization are the recent duties of an intelligent system. While AM for remanufacturing is still dependent on human skills and monitoring, it is important to integrate with AI systems by interlocking and orienting these experiences and knowledge from skilled workers, and this will enhance the whole design and optimization process. One of the interesting applications of AI is sustainable computing. It is based on analysis and evaluation depending on green computing for the elimination of hazardous chemical materials based on an improved algorithm [30]. Artificial intelligence is always deployed to simplify and facilitate the repairing process by providing some opportunities that strengthen automation during remanufacturing and restoration. A deep learning model is usually used for accelerating the topology optimization process. In this method, the configurations of structural topology with the minimum structural deformation are applied under various load conditions. The strategic framework is based on the finite element method (FEM)removal strategy. Two special convolutional neural networks (CNN) and recurrent neural networks (RNN) are integrated into the deep learning model, as well as the long-short term memory (LSTM) [31].

AI can be classified as computational intelligence and symbolic intelligence. Computational intelligence, such as evolutionary programming, artificial neural network, and fuzzy systems, is used for decision making, while symbolic intelligence is used for solving problems based on knowledge [32]. AI has a positive impact on AM, wherein the printability of components can be analyzed and optimized before any postprocessing. Furthermore, the process quality can be controlled and predicted for time-saving. Identifying part functionality, improving quality, and increasing productivity are the main objectives of adopting AI algorithms in AM applications [33]. Combining subtractive and additive manufacturing in the same domain will lead to the exploration and finding of a way to solve some of the optimization complexity by adopting artificial intelligence techniques. These requirements are crucial to assure product efficiency, especially since the target is to return the product as new [34]. Some of the important AI methods used for optimization techniques in AM applications have been summarized and provided in Table 1 according to the author's names, strengths, and main contributions.

Table 1. The important types of AI that are used in AM applications.

AI Model	AI Specifications	AM Applications	Remarks	Refs.
• Particle Swarm Optimization (PSO)	• Works on a simple concept. • No need for big memory. • Inexpensive computationally.	• Employed for determining an optimal design. • Simple coded concept and can be used in lines of code without demanding large amounts of memory.	• PSO generates the optimum data set for the AM model. PSO has a great ability to reduce the number of inputs and obtain an optimum model.	[13,35,36]
• Artificial Neural Networks (ANN)	• Information and communication transmission between the nodes are similar to the principles of the nervous system. • Speech recognition. • Regression.	• Machine learning (ML) is a common application. • Parameters optimization. • Strength of the performance of the process. • Mechanical properties estimation.	• ANN has a great ability to model nonlinear and complex models without limitations on the input–output parameters. Highly efficient in design modeling and predicting the AM complex components.	[29,36,37]
• Genetic Algorithm (GA)	• Built on the principle of genetic reproduction • Comes from the concept of the survival of the fittest.	• Determine optimal product design and optimization. Parameters fitness evaluation. • Flexible and robust. • The ability to explore and solve complex problems.	• GA merges with other algorithms and works as a hybrid AI in AM applications to reduce costs with time-saving.	[7,29,38]
• Fuzzy Set-Based System	• Depends on the input and output state. • Basic control system. • Works depending on the probability of the input and output state.	• Ability to solve the uncertainty of a problem. • Avoids uncorrected judgments. • Ability to find the best design solution. • Decision-making approaches.	• It is commonly used in AM processes to determine the model cost. It is also used in the testing and qualification of additive manufacturing components.	[10,14,39]
• Adaptive Neuro-Fuzzy Inference System, (ANFIS)	• Applies a unique algorithm known as a hybrid learning algorithm.	• Hydrology fields. • Forecasting hourly water levels and rainfall. • Dealing with high nonlinearity such as reservoir operation.	• ANFIS is a powerful tool for modeling, predicting, and controlling many AM processes. It has a high simulation accuracy with limited weaknesses.	[40,41]

AI-based optimization consists of many types, such as fuzzy logic, artificial neural networks, particle swarm optimization, and genetic algorithm. The flow chart processing of the common artificial intelligence used in industrial applications is illustrated in Figures 1–4 [29,36]. The adaptive neuro-fuzzy inference system (ANFIS) is normally used with high nonlinearity applications such as forecasting and reservoir operation. It uses a hybrid learning algorithm. ANFIS input models always involve a human decision, which results in superior performance. Figure 1 illustrates this type of AI.

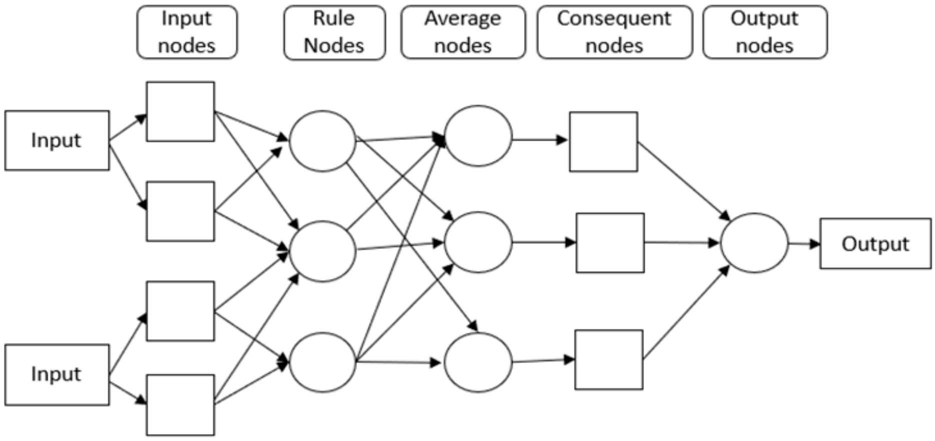

Figure 1. The adaptive neuro-fuzzy inference system (ANFIS) architecture, as adapted from Ref. [40].

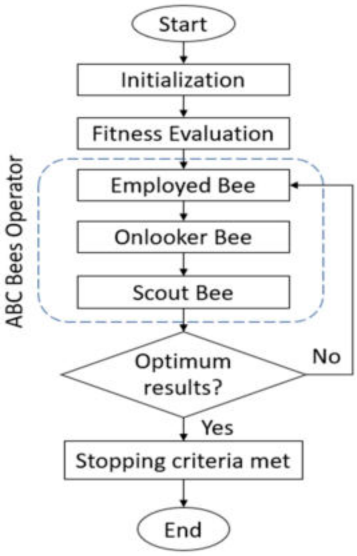

Figure 2. The particle swarm optimization (PSO) operation process, as adapted from Ref. [40].

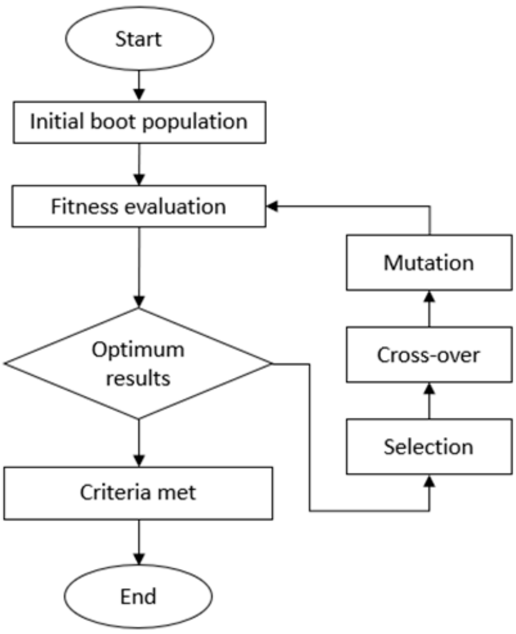

Figure 3. The artificial bee colony algorithm (ABC) process, as adapted from Ref. [40].

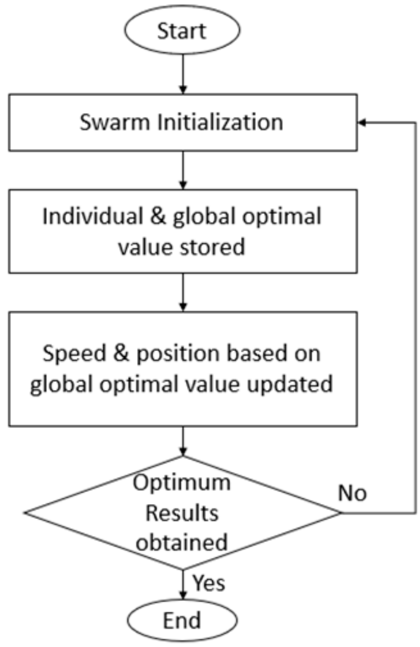

Figure 4. The genetic algorithm process, as adapted from Ref. [40].

Particle swarm optimization (PSO) is an evolutionary method of computation based on the simulation of simple models. The advantages include requiring a smaller memory, higher computational speeds, and easier management. Figure 2 illustrates the PSO operation process.

Artificial bee colony (ABC) is a revolutionary optimization algorithm. It can be defined as a mechanism that occurs from the dynamic interaction between the structure and parts disordered. The flow chart in Figure 3 shows this type of AI.

Genetic algorithm (GA) is a population-based optimization algorithm with a percentage of high reliability. It is a strong optimization algorithm with high performance. This algorithm is always adopted as a strong tool in the AM optimization process. The flow chart in Figure 4 shows the GA process.

AI is new support for AM in optimizing components and is considered a helpful tool to enhance the CE [2]. The production of components using AM needs high levels of specialized knowledge. Consequently, adopting AI can help in solving these issues by reducing the conventional work performed manually through access to large amounts and high accuracy of data. AM involves many stages, such as the preparation of the 3D CAD model, prototyping, and production. The domain of 3D printing is restricted to product geometry and material type. Implementing AI to minimize computational time becomes a necessity to speed up the remanufacturing process [11]. For optimum weights computing, the algorithm network such as ANN is built firstly as a training model. The model weight is a set of random values, and this training model is considered completed whenever it approaches the optimal target. The property of a quick solution to the optimization problems of 3D printing without the need to define an algorithm is one of the significant features of the ANN method [29]. The useful applications of AI in AM should focus on increasing the tool life predicting accuracy, minimizing the cost, and decreasing manufacturing defects. The sequential strategy and systematic guideline for enabling AI technologies as an industrial ecosystem include four main sequence steps: data technology, analytical technology, platform technology, and operations technology [42].

AI and AM can be integrated toward more innovation, efficient production, and enhanced competition between industrial companies. Scalability and compatibility between AM with AI increase efficiency by increasing the decentralized production capabilities with respect to volume and time [9]. Machine learning (ML) techniques such as AI networks and ANN are highly suitable for solving problems of AM, especially in the area of control and monitoring due to their labeled datasets and availability. The lack of enough databases and the shortage in the availability of accurate data are considered the main challenges in the advancements of ML for AM processes. Other reasons involve a lack of standardization for handling high-velocity and high-volume databases in exact time [43]. AI-based methods are more capable of replicating expert humans in the decision-making and repair process. Additionally, it is capable of responding to large quantitative and qualitative data at the same time.

4. Design Optimization Methods for Repair and Restoration Using AM

Optimization is defined as the best way for a better solution to recover the maximum functions under specific conditions. Design optimization is the process that leads to eliminating or removing the design constraint and limitations that were previously encountered during the part manufacture with affordable cost. The potential planning and implementation in AM are enhanced by adopting AI for design optimization, monitoring process, and the detection of defects [44]. Design optimization of parts is enhanced using AM because the designer gains a wide space of freedom when the design process is fully computerized. The suitable optimized design is considered an important step in identifying the AM objectives. Optimization methods are great tools that are usually used within AM applications to emphasize the component's value in many disciplines, such as minimizing the mass and cost and maximizing the production and profits [28]. Obtaining a lightweight part while maintaining the same performance and mechanical properties is significantly achieved by adapting the design optimization method. This includes stripping away some of the unnecessary metals to meet the optimum design. Improvements in design include minimizing the weight, strength enhancement, and reducing the residual stress [45]. The criteria in decision making are based on account of different parameters and give the solutions that have the best fit with these parameters. It starts with the best-optimized design by comparing the weight, manufacturing cost, strength, and surface quality. The criteria weight factor is calculated according to the strength, weight, and customer's point of view. The systematic procedure for selecting the optimum design based on specific criteria is presented schematically in Figure 5 [46].

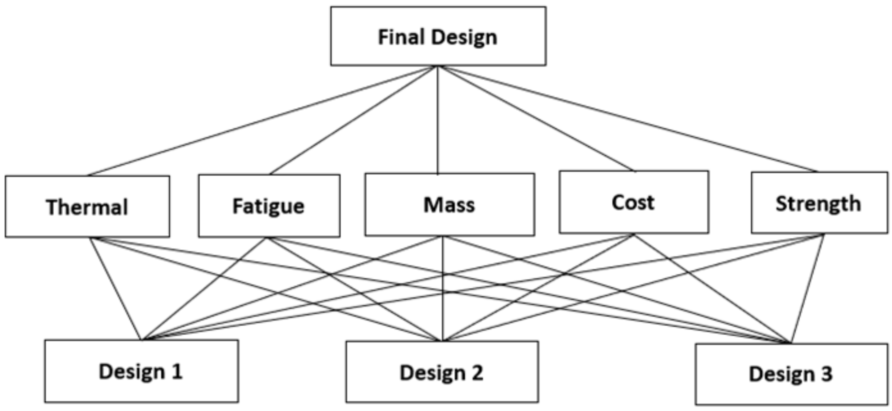

Figure 5. Multi-design optimization analysis, as adapted from [46].

Restoration design should take the option of product disassembly in the future as a targeted strategy to reach the optimal design. Consequently, product restorability must involve all of the concerned aspects, such as conditioning and the machining process, to ensure appropriate component recovery. It is necessary to be sure that the design integrates well with some processing repairs.

AM is classified as a sustainable method and mostly linked to a CE besides many benefits involving time and cost-saving. There is more than one proposed technique dealing with AM including mathematical and optimization techniques; however, a wide effort is still required in other areas, such as design, for supporting this process [35]. In the AM industry, any suggested design for complex products should be considered as an approach toward repair, restoration, and tool longevity. The principal path in design for restoration can be subdivided into the design for repair, the design for remanufacturing [47], and the design for refurbishment [48].

The advantages of AI techniques in AM are attributed to high flexibility in solving complex design issues with its strong capability in strengthening efficiency and executing high accuracy in design optimization. To sustain the supply chains of the spare parts, specifically the complex parts, redesigning and reconfiguring for AM can extend the product life cycle to maintain materials resources and keep simpler and shorter supply times. Design for AM is focused on extending the part functionality toward high performance in the AM domain. Building a design method for AM based on the growth of internal stresses parallel with part repair and shape morphing optimization will enhance the efficiency and effectiveness of the process [49].

Design for AM framework includes information on component geometry, feedback information, and stepwise evaluation during each operation step. The lack of understanding and knowledge is recognized as one of the key problems relating to the design and optimization in the AM domain [50]. Design optimizations based on AI techniques for AM applications are crucial due to their impacts on the whole efficiency and circular economy. It is a priority to optimize the essential design to enhance the efficiency of the repair and restoration process in additive manufacturing. It is reported that the use of design and optimizations of AM is still limited for many reasons. It concluded that the use of AI in design optimization will facilitate and remove many obstacles and limitations in front of an efficient restoration process [51]. The motivation behind using the AI technique in AM is to improve and ensure the quality of the parts, relying on its automatic ability in predicting and improving quality by preventing design and production defects. AI is widely used in AM execution and is used as an assistance factor in AM planning, e.g., the design process [44]. In many engineering applications, optimization is indispensable, especially in mechanical design. The critical factor in optimization time is the number of design evaluations. Large and multiobjective optimization algorithms require highly expensive computational analysis [52]. AM is a fully automated process and digital technology through all steps from the design stage to the final printing, so the development of data networks of machine learning and artificial intelligence leads to high progress in the AM industry [41]. Design for AM means optimizing all steps followed in the basic manufacturing process of the intended product. It includes three essential steps: materials design, process design, and component design. The design activities include three sequence levels, as illustrated in Figure 6.

The classification of design optimization is usually based on different methods. It depends on many orientations, especially whether the optimization is a multiobjective or single-objective problem. There are many disciplines in design optimization, such as multidisciplinary optimization, optimization algorithms, and structural optimization. There are many algorithms for solving optimization problems. Evolutionary optimization algorithms (EA) such as GA are used to mimic evolution to estimate the optimum design. It is robust and can be adopted for the evaluation of a high number of design problems until it reaches convergence values [7]. One of the important tools for the planning, designing and optimization of multiobjective and complex problems that emanate from AM is EA. It is a subset of the many iterations and computing processes associated with machine learning. EA is a branch of artificial intelligence and becomes more necessary in the design process coinciding with the evolution of hybrid manufacturing [6]. The powerful computational model artificial neural network ANN, which consists of a network of nodes, is very useful in solving some AM problems and is used for making good predictions. The two categories of machine learning, supervised and unsupervised learning, are adopted for high-level classification, predictions, and regression. Artificial neural networks ANN have very good capabilities for solving many AM problems and especially for complex task processing [43]. Both artificial intelligence and machine learning are integrated and contribute to AM development.

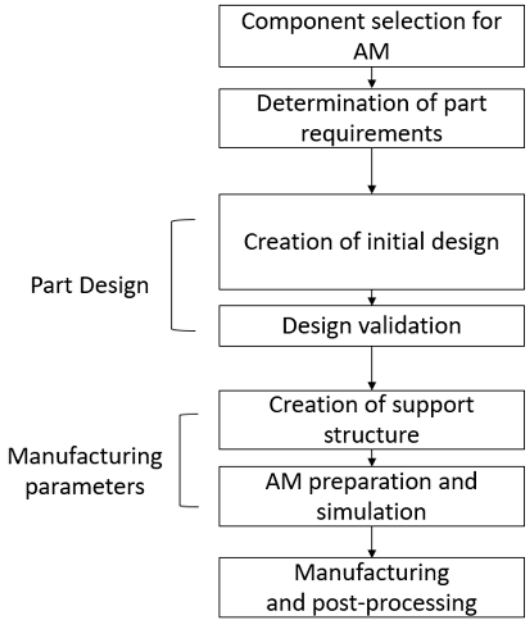

Figure 6. Design activities that form the art design process for AM.

Systematic design optimization is proposed to enhance the performance of the AM process by considering and enabling product changeability during its working life, not just in the design stage, to maintain better performance [53]. Multiobjective optimal design based on genetic algorithms is used for optimizing the performance of a planetary gear reducer [54]. Design for multiple lifecycle strategies is not certain due to a lack of clarity in the expected operations that are required for each step of recovery as well as the unclear expectations in quality [54]. The most evolutionary optimization technique is the genetic algorithm. It has always been adopted to optimize many complex problems. The most accurate description refers to GA as the survival of the fittest as an optimization technique built on evolutionary rules [54]. The redesigning of the AM process depends on many variables [55]. The process can make parts more expensive than the original part. AM can reduce the mass depending on print speed and part size.

Two methods are used in implementing shape optimization. The first is called designer-driven shapes, which depends on the principle of optimizing the design by reducing the mass and printing time by using the shape lattice to make self-support. The second one is the process-driven shapes, which uses topology optimization to reduce the mass [35]. J. Kranz et al. [21] presented layout design guidelines for laser AM of lightweight structures through multiple iterations to offer designers a buildup of their design according to AM restrictions from the first stage. B.Thamaraikannan et al. [56] used a hybrid teaching–learning-based optimization TLBO algorithm to investigate different design optimization problems to solve some technical problems such as volume minimization of a closed coil helical spring, weight minimization of a hollow shaft, and weight minimization of a belt-pulley drive. It is an evolutionary algorithm and has been proven to be more efficient than some existing optimization techniques such as hybrid PSO, ABC, and GA. In many engineering applications, the design optimization process is performed implicitly. It often depends on modeling and judgment to reach the optimal solution. The availability of quantitative models is important to obtain the optimal solution. The most important step in design optimization is to validate an accurate model. For example, in additive manufacturing, to minimize the cost, it is important to be able to calculate the actual cost from the beginning. Despite some drawbacks in the analysis program, especially for that which require greater execution time, GA is widely adopted in the design optimization of many AM applications due to the superior options, such as the trial-and-error search and inheritance characteristics to perform best designs, such that the genetic algorithm can build remarkable results faster for problems with a large combinatorial domain search [57]. Maryam Daneshi et al. [58] developed an optimization tool framework based on hybrid machine learning which can be used in the design of solar shadings and the evaluation of their efficiency. The results obtained estimation functions that are suitable for finding the solution in machine learning and can generate a consistent database toward optimal models.

Redesign and optimization are used to upgrade the repair components by using a hybrid AI method through evolving the material distribution within the specific design domain to maximize the material fraction. A hybrid algorithm is a numerical tool used for forecasting and suggesting better improvement parameters that lead to optimal material distribution [59]. Metamodel-based design optimization uses multidisciplinary design procedures to approximate, simulate, and compute some of the expensive models. In comparison with the genetic algorithm, the required number of simulations to implement the optimization is too low for the specific algorithm to implement the optimum solution [60]. Vladislav Andronov et al. [61,62] proposed and investigated an optimization methodology to reduce production costs and increase productivity through additively producing a tool steel layer with a thickness of 100 µm. The employment of hybrid AM by combining additive and subtractive manufacturing reveals great improvements and enhanced product quality.

5. AI-Based Design Optimization Methods for AM Repair and Hybrid Method

The term "hybrid" refers to merging more than one algorithm technique to generate a new optimizing technique with gaining new features better than the individual method. The most significant characteristics of hybrid algorithms are the few iterations and computational steps, high convergence speed, and low effective cost compared to other algorithms. The parameters of any suggested hybrid algorithm are defined as the number of possible answers and the main objective for implementing this algorithm. The possible answers (iteration numbers) are defined as a matrix. The ability to solve many complex issues efficiently has brought a lot of attention to hybrid AI in recent years, especially in design and optimization applications. It is now possible to diagnose the failures and adjust the effecting parameters to find suitable solutions by creating algorithms. Developing expert systems using AI techniques is also significant while the expert system can develop as an expert-controlled system [51]. Despite the advantages of using AM technology, which include cost and time-savings, there are deficiencies in dealing with components of complex geometries. Dealing with AM in the aspect of design and optimization is crucial to enhance this restoring method and support the designer in concentrating on complex shapes and restoring them effectively. Future research is required on design optimization for AM to provide a valuable vision for this industry [63]. One of the important aims of the design for optimization approach is the devising of components according to customer needs and making necessary modifications without interventions from humans.

Some reasons, such as the difficulty of evolving efficient design thinking, led to the recording of several limitations in AI-based design optimization related to component implementation in AM [64]. Consequently, developing and integrating hybrid AI techniques are considered crucial steps toward developing AM technology. Some other challenges, such as the generalization of genetic algorithms, are reported with several types of AI optimization such as genetic algorithms. Moreover, AI optimization has some limitations, including time costs, due to the accuracy of the solution requiring to be rerun to the basic model many times to approve the solution according to the basic hypothesis and parameters. In the optimization process using a hybrid algorithm, the type of trigger, number of generations, and population size are essential to making decisions in GA, while the neuron's number and type of network topology are used to make decisions in an ANN type [51]. Applications of AI in the optimization AM process have been widespread in recent years according to many literature indications. The literature recently revealed that the method of hybrid optimization has shown a better capability with accurate results. Merging more than one technique as a hybrid technique is a good solution to integrate, increase capability, and enhance the strength of AI in solving complex problems. However, the important aim of any design optimization method for the restoration process is to be sure that the process is efficient regarding cost and time. The powerful optimization techniques abridge thousands of evaluation processes in fewer steps and in a shorter time.

An optimization method was implemented on a worn crankshaft according to the theory under uncertainty conditions resulting in a 5.6% cost reduction, 7.3% saving time, and 2.5% quality improvement [64]. Aydin Azizi utilizes a hybrid AI technique in modeling to perform a hard learning optimization from two different algorithms with a universal manufacturing system, and the result was successfully implemented. The design of a hybrid cellular model for sustainable manufacturing–remanufacturing was built to increase the reliability and flexibility of this process [28,65]. Minimizing total costs concerning the supply chain and the hybrid cellular system was the main function of this hybrid model [66]. Min-Yuan et al. [67] approved that the hybrid particle bee algorithm PBA was formed by combining particle swarm optimization and bee algorithm BA to facilitate layout design problems. It has been found that this algorithm has better performance than some other techniques in terms of benchmark functions and the ability to solve engineering problems with accurate dimensionality [67]. A general hybrid model involving a combination of dynamic programming and genetic algorithm is used in design optimization to develop an energetic model for hybrid electric vehicles by minimizing fuel consumption and battery size. The outcome was a 5% reduction in fuel consumption and minimizing the battery size [36]. Virtual model links that are used to connect the components will be inserted inside a binary-level optimization and then utilized by the use of genetic algorithms in the optimization process. This general hybrid model is also used to calculate fuel consumption and dynamic performance [36]. The conventional method was fused with the evolutionary computing method to develop a hybrid system for computing, optimizing, and forecasting climate and water resources. Genetic algorithm and genetic programming (GP) were adopted together to form a hybrid algorithm for optimizing the reservoir operating system [40].

Along with probability, statistics, and classification, AI also involves many techniques and tools that are considered very suitable for logical regression and optimization. AI models can be classified into two main categories, supervised machine learning (classification and regression) and unsupervised machine learning approaches (clustering and optimization algorithms), as illustrated in Figure 7 [40].

Multi leader optimizer (MLO) is an optimization algorithm able to provide appropriate and more competitive solutions for the optimization of problems by comparing and analyzing many iterations of results until reaching the appropriate solution [68]. Ghoreishi et al. used advanced meta-heuristic optimization as a hybrid algorithm by combining the gray wolf optimizer GWO and sine cosine algorithm SCA for solving the problems and optimizing the antenna architecture design [64]. This optimization algorithm is a versatile, practical, and reliable platform for optimizing design parameters [69]. Aydin Azizi [28,52] used a ring probabilistic logic neural networks (RPLNN) optimization technique with redundant antenna elimination (RAE) to compose a new hybrid technique to calculate the required number of antennas that need to be deployed and expand the coverage area for radio frequency identification [28].

A combination of hybrid co-evolutionary genetic algorithms with a fuzzy formulation is proposed for the optimization of gas-production systems. The newly formed algorithm is utilized for improving the allocation and production rate as well as minimizing the operation costs. The network representation of this optimization system as a case study for synthetic gas gathering is studied by Park et al. [38].

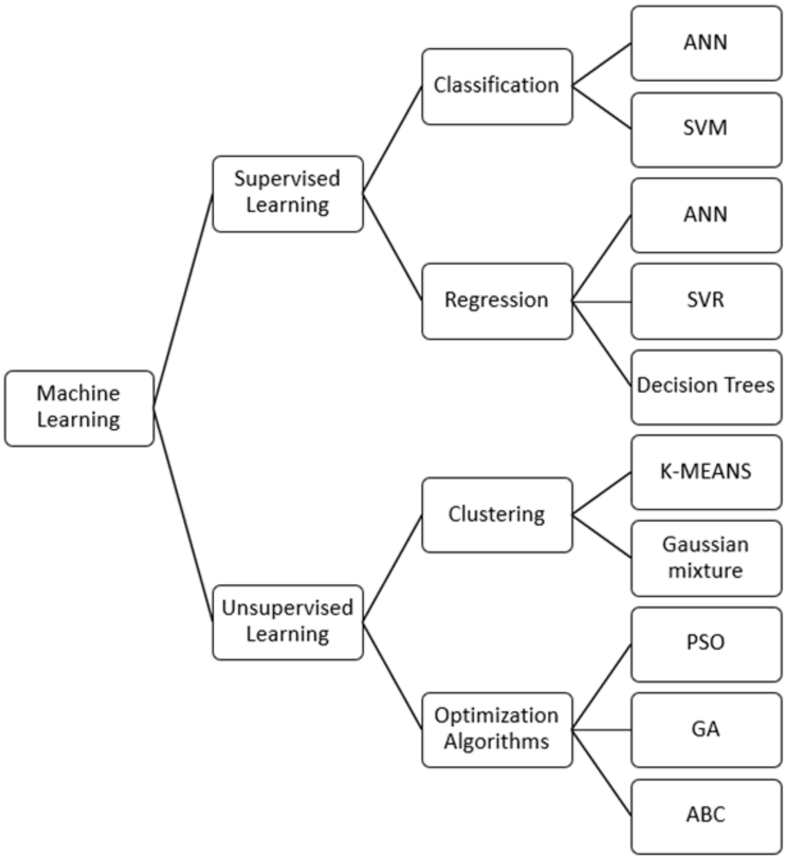

Figure 7. Machine learning classification, as adapted from [40].

Maryam Daneshi et al. [58] used the NSGA II algorithm with machine learning models as a hybrid tool in the design, development, and evaluation of the performance of static solar shadings. The findings reflect the high activity of this tool, which is capable of the design and evaluation of solar shading in various spaces [58]. In hybrid AM, instead of the raw material, manufacturing starts from the point at which the part lost its main function. The deposition of material layers is directed toward the damaged zone to compensate for the geometry shortage [30]. The damaged component will either be repaired or the functionality of the part will be upgraded, as shown in Figure 8.

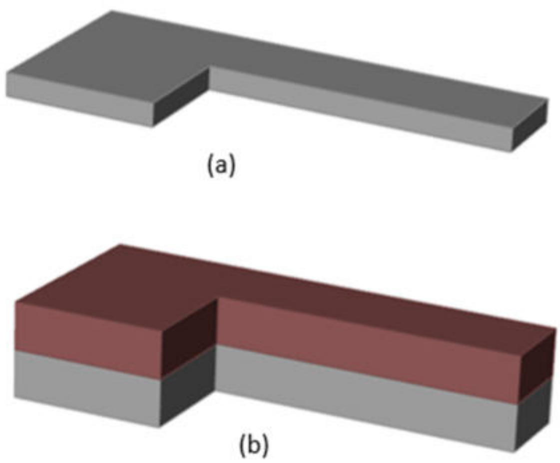

Figure 8. Design domains arrangement: (**a**) design domain before AM and (**b**) additive manufacturing design domain.

Three AI approach techniques (purely AI, integrated, and purely analytical) are combined for optimizing PSS. A fuzzy system is used to solve linear relationships between complex variables and set the optimal parameters [26]. An ABC algorithm and an ANN were combined as a hybrid AI to predict and optimize the penetration rate in a gas well, and the results were very useful [70]. The genetic algorithm was merged with particle swarm optimization to reimburse some deficiencies in genetic algorithms, such as slow calculation speed. The new hybrid optimization algorithm was generated with a reliable solution and fast calculation [30]. Ivan Peko et al. [39] used the multicriteria decision methods ranking organization method (PROMETHEE), analytic hierarchy process AHP, and fuzzy AHP for solving the AM selection problems. Optimization algorithm-based finite element analysis and genetic algorithms were applied as the best combination to reduce the weight problems and minimize the manufacturing cost limitation [71]. The ANN algorithm was fused successfully with GA for the design optimization of the quality of laser cutting to predict and determine the set of parameters responsible for quality optimization and to predict output findings [37].

The main aim and applications of AI are to reduce the costs of the computational optimization process. CAD modeling is used for creating and evaluating parts or products, while design optimization is adopted to find better design fits to be set for specific requirements. Design optimization tools can improve assembly time and are better at building by reducing the number of items in a product in an existing assembly by performing a kinematic analysis to ensure the best-integrated functionality [7]. This optimization process is presented in Figure 9 [70].

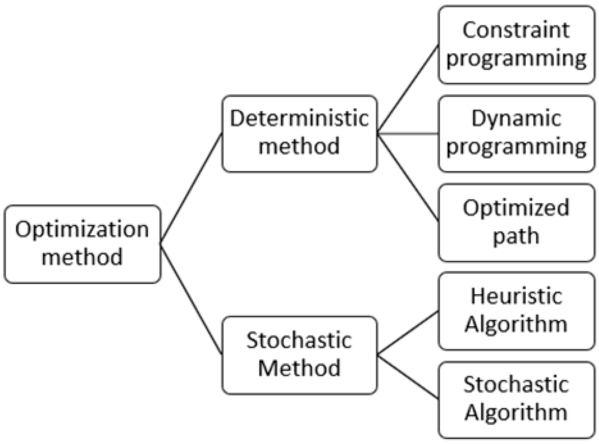

Figure 9. Optimization process, as adapted from Ref. [70].

The main aim of the hybrid algorithm in the optimization process is to reduce computational costs. The comparison between optimized models and stand-alone models is illustrated in Figure 10 [40].

Hamid Moeeni et al. [72] merged the ANN with a GA as a hybrid model for forecasting, examining, and comparing the monthly inflow to a dam. In this search, a novel hybrid ANN–GA has been employed. The procedure of the hybrid (ANN–GA) used consists of multilayer neural networks such as one or more input, hidden, and output layers. The information presented in Sections 4 and 5 regarding design optimization methods for repair and restoration using AM and AI-based design optimization methods brings us to the recommended solution of combining GA and ANN to form a hybrid method for repair and restoration using AM, as presented in Figure 11. This recommendation is explained in detail in Section 6 for future research directions.

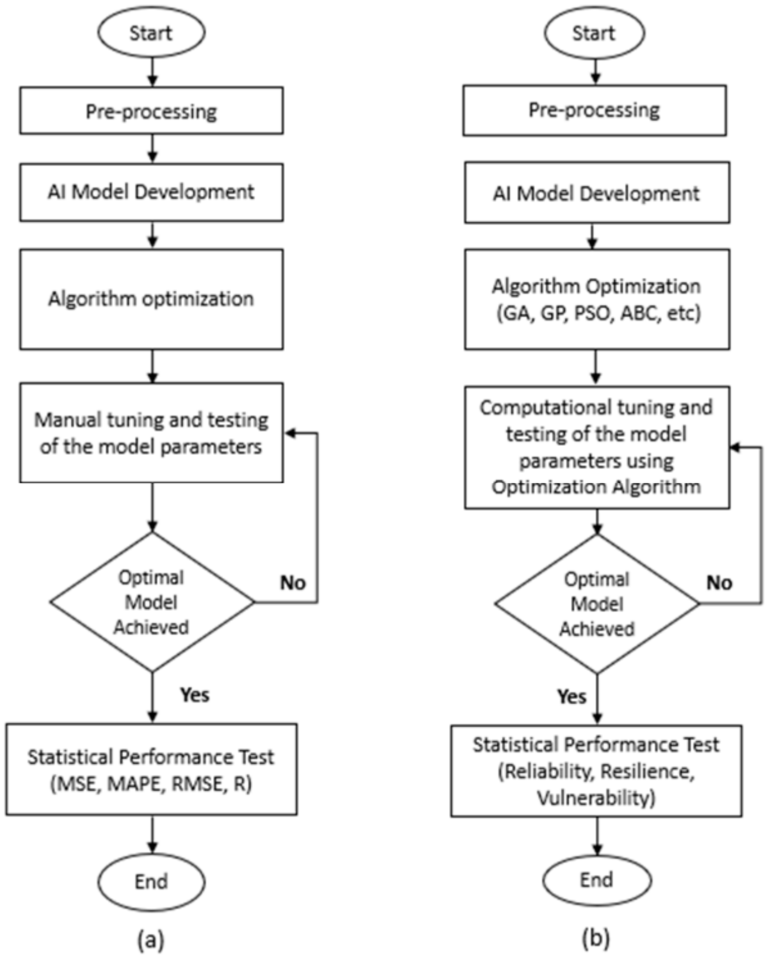

Figure 10. Comparison between (**a**) stand-alone model and (**b**) optimized models, as adapted from Ref. [40].

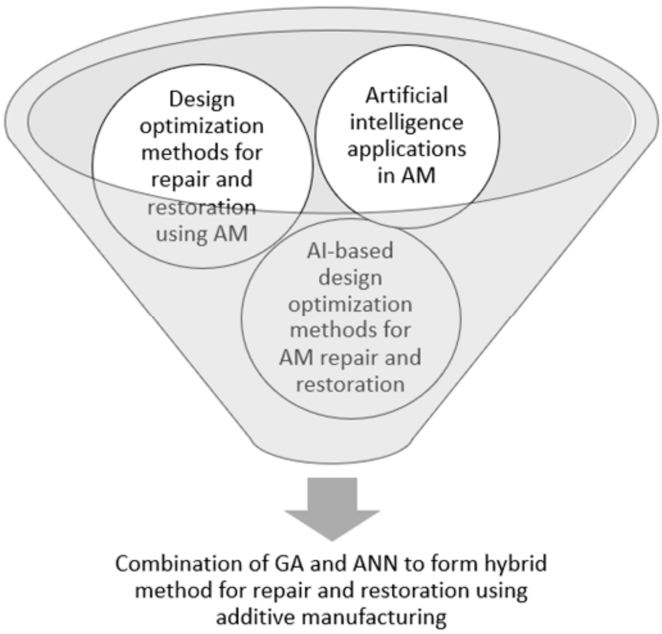

Figure 11. Recommendation for the hybrid method of repair and restoration using AM.

6. Discussion and Recommendations for Future Research Directions

In this review, exploring the important impact of AI on the AM domain is the main objective of this work. Despite some downsides and difficulties of integrating AM in industry with current trends of industrial applications, especially small and medium volume production, it is obvious that AM is expected to be the main method in the restoration of complex components [73]. To name a few, repair and restoration do not require additional tooling, and this will lead to further reductions in time, energy consumption, and production costs. Accordingly, developing guidelines and standards through real collaboration and commitments between industrial companies becomes an urgent mission [74]. AM uses far less energy than traditional machining in terms of personnel and tooling [75]. Design optimization methods in repair and restoration can reduce the weight of parts while maintaining the same mechanical properties. Many works in the literature confirm that artificial intelligence algorithms can confirm the optimal orientation for the restoration process of many complex parts.

Most of the design optimization-based algorithms used by researchers are stand-alone algorithms due to the complicity and high computational time cost of combining more than one algorithm for this purpose [76]. Optimization problems are classified as highly provisional problems and require a wide knowledge of many disciplines. Consequently, the combination of adequate techniques is the key to solving these problems and achieving optimal optimization. Hybrid AI techniques are a combination of some individual techniques that benefit from their advantages and overcome the weaknesses of each stand-alone technique. This will develop a significant feature and add important values that lead to more motivation for the overall AM process [3,77]. Composing functional hybrid techniques for optimization purposes depends on the strong features embedded in each one. For example, the hybrid AI that results from the merging of ANN with the hybrid genetic algorithm will utilize the fast filter of GA and fast selection with accurate calculation of ANN to compose an effective optimization technique in providing a high-accuracy prediction. Some reviewers concentrate their research on the determination of the build orientation-based design algorithm of the final product, which has a high impact on the overall AM quality [78,79]. Another example of adopting a hybrid technique from many researchers for design optimization purposes is the use of the ANFIS technique, which is a combination of ANN and fuzzy logic (FL) for solving geological problems and for achieving both the quantity and quality of the mining process [80]. The FLC is flexible and has an intelligent strategy, an application-appropriate interface, an aggregate of several control algorithms, and a straightforward computing and learning system. It is also very versatile [81].

Knowledge-based optimization techniques such as ANN, GA, particle swarm optimization, and fuzzy logic, when hybridized with other algorithms, can be deployed to provide a professional system to optimize the design parameters in the restoration process and can offer decision making. Many types of research confirm that optimum repair using AM has to be built on restoration strategies from the first design step according to the part complexity and system capabilities. The integration between AM technologies and AI in many disciplines such as ML adds significant value to the overall design procedure and enhances process efficiency. AI can be deployed in numerous AM applications, such as error detection, prediction as well as decision making. Many types and categories of AI techniques can be deployed in many AM domains, such as ANN, genetic algorithms, fuzzy logic, and particle swarm optimization, in addition to many other hybrid techniques. Each of these techniques has its own specific strength, weakness, and applications. While the main target of adopting the AI technique in the AM domain is to support and achieve better design optimization and facilitate the overall restoration process, especially for complex geometries, it is necessary to merge more than one technique in a hybrid method which comprises the important strength characteristic of each stand-alone algorithm. The effectiveness of hybrid techniques is attributed to their important ability to predict the orientation of the optimization process and their ability in solving optimization problems. The expected hybrid technique should have scalable knowledge with a reliable database that enables decision making about whether the specific part is capable of being restored to the original case or not. Moreover, further deployment of the hybrid technique-based design optimization should be built from the first step on the ability to support the product design and cost optimization for restoration purposes.

Many of the above aspects regarding repair and restoration using AM have recorded some restrictions and limitations in the optimization cost. Therefore, to gain advantages, design optimization for AM processes needs to concentrate on high-value parts and complex geometry components. Based on the findings presented in this review paper, the following are key points and recommendations for future work directions in the design optimization of AM parts for repair and restoration based on AI.

- The mechanical properties of the parts manufactured using AM are influenced by the manufacturing parameters used, such as temperature, scanning speed, hatching distance, and energy density. Future research should concentrate on optimizing these manufacturing parameters to obtain the best mechanical properties as well as to further reduce cost, time, and energy consumption.
- Optimization for AM needs to focus on removing the unstressed segments in a specific part and then make a comparison before and after to meet the functional requirements to create the optimized geometry.
- The design Optimization for AM should be decided and recommended from the first design step.
- Future research needs to adopt many missing issues related to conducting AI with AM. These missing aspects include the application of AI in cost estimation, forecasting the mechanical properties, raw material assessment planning, and postprocessing improvement.
- Circular strategies should follow comprehensive guidelines in conjunction with companies' annual planning in dealing with the movement of materials and resources toward recirculation and reuse by adopting a design optimization-based hybrid method for the restoration of all complex components.
- Combining algorithms to form a new hybrid can add significant value to the AM process.
- Optimization is always required from AI models. Forming hybrid models by merging the stand-alone AI with optimization techniques is a survival collar for solving complex issues related to the AM industry.
- While many products are not designed for the AM process, there is also no feedback from companies wishing to redesign. Consequently, and toward an efficient design for remanufacturing, it is widely advised to feed remanufacturing companies with information relating to the specific restructuring components.
- It is important to realize that for any specific part under restoration, the product scale is a significant issue; hence focusing on controlling the length scale to avoid a small thickness, which is hard to machine, and finally, the overall size of the part should not fall lower than the printing machine resolution.
- The ANN algorithm can simplify the models, shorten the necessary time for building the network and minimize the number of input variables toward efficient optimization, while the genetic algorithm is used for reducing the number of variables.
- Finally, combining the GA with an ANN algorithm to form a hybrid algorithm is recommended for solving the optimization problems regarding the AM process and emphasizing material strength.

7. Conclusions

This review paper presents a wide explanation of many aspects relating to AM technology for repair and restoration using AI in design optimization, focusing on specific elements, such as design objects, optimization procedures, and applications of AI (hybrid method) in the AM domain. AM is widely reported in many reviews, and the need for further exploration of the overall influence and impacts of new applications in AI should be fully understood. The guidelines proposed are hybrid; however, at the same time, it is possible to detail and tailor them according to the available restoration domain. It is worth noting that not all materials are suitable for optimization. As a priority, it is necessary to make a database of information and knowledge involving such types of materials.

There is no specific or systematic methodology to empower industrial designers in the field of AM for the redesign and optimization of existing components. The literature survey led to addressing and identifying some challenges that are still not solved which require more research to facilitate and overcome the limitations of implementing AI tools into AM applications. However, there are also some success stories for the adaption of AI as an efficient analytical tool, and in the interaction between AI and AM, such as in robotics applications and machine learning. The study concluded that components intended for restoration are advised to be designed basically for these purposes, to recover and extend the product EoL in the circular economy. Sharing information between industrial companies and stakeholders for the data, especially for high-value products, to enable a time calculation to be made for the remaining useful life of components. AM is still without standardization, and this is one of the limitations; a lack of a database of information regarding the remaining useful life of complex components increases the challenges for the adoption of this method. The programming, digitalization, and the IoT in design optimization lead to empowering AM toward a more effective life cycle and circular economy. AI is rarely used to predict parts orientation or to estimate the cost. Execution processes, such as defects and quality monitoring, are the most common applications for AI in AM.

It can be concluded that large parts are not suitable for redesign optimization by AM processing because of the prohibitive costs; however, it can be used to increase the performance of the part. It is worth noting that there are still other gaps and challenges concerned with estimating the remaining useful life of complex components at different stages of their working life. As well as the basic concept of design optimization in the AM domain and tool development, it is also concerned with the environment in reducing energy consumption, materials, and pollutants. For an efficient optimization process, it becomes a priority for researchers to adopt the early design for the restoration and circular economy. Hence, planning for future recovery operations during the initial stages of product design is an important mission.

In conclusion, designing an optimization-based hybrid AI for restoration through AM can enhance the design parameters and overall product quality. Combining subtractive manufacturing and AM in the same domain will lead to the exploration and discovery of solutions to solve some of the optimization complexity by adopting artificial intelligence techniques. These requirements are crucial in assuring product efficiency since the target is to return the product to its as-new condition.

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