Artificial Neural Network with Genetic algorithm as a hybrid method for optimization of additive manufacturing process

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Abstract

Additive Manufacturing (AM) is a state-of-the-art technology that can create more accurate and customized geometries. However, challenges such as dimensional inaccuracies and material inconsistencies remain significant hurdles to achieving optimal performance. This chapter examines the deployment of Artificial Neural Networks (ANN) and Genetic Algorithms (GA) as hybrid optimization methods to improve AM processes in a wide range of applications. The study uses deep learning-based optimization methods to improve dimensional accuracy, thermal properties, and material properties.

The study explores integrating Backpropagation Neural Networks (BPNN) and GA as a hybrid optimization strategy for AM. BPNN enhances predictive accuracy by identifying non-linear relationships, while GA improves global search capabilities, prevents local minima, and optimizes AM process parameters. This combination speeds up convergence, lowers error rates, and enhances generalization in predictive modeling.

Furthermore, this study presents a novel Genetic Algorithm-Based Data-Driven Process Selection System for AM in Industry 4.0. The system utilizes CAD data and user preferences to classify AM processes. The findings demonstrate the potential of AI-driven hybrid optimization in AM, paving the way for intelligent, automated manufacturing. This approach can be extended to various industries, including aerospace, healthcare, and automotive, where

precision and reliability are critical. GitHub link for the experiments performed: https://github.com/saksham1702/ANN-GA/tree/master

Keywords: Additive Manufacturing, Genetic Algorithm, Artificial Neural Network

1. Introduction

Additive manufacturing (AM) has undergone a transformative evolution since its inception in the 1980s, progressing from rudimentary prototyping tools to sophisticated systems capable of producing high-performance industrial components. This evolution has been paralleled by advancements in computational intelligence, particularly the integration of artificial neural networks (ANNs) and genetic algorithms (GAs), which now form the backbone of modern process optimization frameworks.

The synergy between these technologies addresses critical challenges in AM, including parameter optimization, defect minimization, and material efficiency, while enabling unprecedented levels of design complexity. Recent research demonstrates that hybrid ANN-GA systems reduce trial-and-error experimentation by up to 70% while improving the mechanical properties of printed parts by optimizing melt pool dynamics and thermal gradients [1–3]. This chapter examines the historical trajectory of AM, the imperative for intelligent optimization systems, and the mechanisms through which ANN-GA integration redefines manufacturing capabilities across aerospace, biomedical, and automotive sectors.

Furthermore, the integration of ANNs and GAs in additive manufacturing has catalysed a paradigm shift from reactive process control to predictive and adaptive optimization. ANNs, with their ability to learn complex nonlinear relationships, are particularly well-suited for modeling the intricate dependencies between process parameters—such as laser power, scan speed, and layer thickness—and final part quality. When coupled with GAs, which effectively explore large solution spaces through evolutionary strategies, the combined system offers robust solutions that adapt to various manufacturing scenarios. This convergence not only ensures higher precision and repeatability in AM processes but also significantly reduces energy consumption and material waste by guiding the system towards optimal process windows.

As industries increasingly demand customized, high-performance parts with reduced lead times, the adoption of intelligent AM systems is becoming indispensable. In sectors such as aerospace and biomedical engineering, where performance and safety are non-negotiable, ANN-GA systems contribute to the fabrication of lightweight, structurally sound components with minimal post-processing requirements. Moreover, the capacity of these systems to accommodate real-time feedback and online adjustments is paving the way for closed-loop manufacturing environments. This chapter delves into case studies and current trends that illustrate how ANN-GA-driven AM is transitioning from research labs to mainstream industrial deployment, thereby shaping the future of digital manufacturing.

2. Evolution of Additive Manufacturing (AM)

2.1. From Stereolithography to Multi-Material Fabrication

The origins of AM trace back to Chuck Hull's 1984 invention of stereolithography (SLA), which utilized UV lasers to cure photopolymer resins layer by layer [https://www.mdpi.com/1424-8220/24/9/2668. Early systems focused on rapid prototyping, with limited material choices and resolution capabilities. By the 1990s, technologies like selective laser sintering (SLS) and fused deposition modeling (FDM) expanded material diversity, introducing polymers such as ABS and nylon [https://www.researchgate.net/publication/372271639_History_of_Additive_Manufacturing.
However, these systems struggled with anisotropic mechanical properties and surface roughness exceeding 20 µm, restricting industrial adoption [1].
The 2000s marked a turning point with the advent of direct metal laser sintering (DMLS) and electron beam melting (EBM), enabling high-strength titanium and nickel alloy components for aerospace applications [https://www.mdpi.com/1424-8220/24/9/2668 Concurrently, advancements in computational modeling allowed for preliminary thermal stress simulations, reducing warping defects by 30–40% in early iterations [4]. By 2020, multi-material 3D printing emerged, combining metals, ceramics, and polymers within single builds—a feat enabled by real-time process monitoring systems [5].

2.2. Material Science Breakthroughs

Material innovation has been pivotal to AM's evolution. While early systems relied on thermoplastics like PLA, modern AM incorporates:

- High-entropy alloys with tailored grain structures for extreme environments
- Bioresorbable polymers for patient-specific medical implants
- Graded composites with spatially varying mechanical properties [https://pmc.ncbi.nlm.nih.gov/articles/PMC9656270/ [5]

These advancements necessitated precise control over process parameters—a challenge traditional empirical methods could not address. For instance, inconsistent laser power in DMLS caused porosity rates to exceed 8% in early titanium prints, prompting the shift toward data-driven optimization [3, 6].

2.3. Importance of Process Optimization in AM

AM's parameter space is notoriously complex, with variables like laser power (100–1,000 W), scan velocity (0.5–10 m/s), and layer thickness (20–100 µm) interacting nonlinearly to influence outcomes. For instance, deviations in hatch spacing by 10 µm can alter residual stresses by ±200 MPa, directly impacting fatigue life [3]. Traditional design of experiments (DoE) required 500+ trials per material-system combination—a costly and time-intensive process [7].

The consequences of suboptimal parameters are severe. In laser powder bed fusion (LPBF), improper energy density leads to keyholing (excessive melt pool depth) or lack-of-fusion porosity, which can

reduce tensile strength by 30% [3]. A 2023 study on FDM-printed polycarbonate demonstrated that ANN-GA optimization improved natural frequency by 26% compared to traditional methods, primarily by optimizing raster angles and air gaps [7].
Such advancements underscore the necessity of intelligent optimization frameworks to mitigate defects and enhance reproducibility.

3. Artificial Neural Networks (ANNs) in Additive Manufacturing

Artificial Neural Networks (ANNs) [8] are part of machine learning algorithms that mimic the human brain. They consist of brain-like simplified versions of neurons that are stacked together to form layers of neurons or perceptron, which form various interconnected layers. Perceptron information and adjust their parameters based on the given training data. Due to their ability to understand complex relations, they find their way into various applications like image recognition, natural language processing, and industrial automation. In the context of Additive Manufacturing (AM), ANNs can play an important role in optimizing the production process. By analysing and training from historical data, ANNs can preanalysingting parameters, which would help minimize defects and enhance material efficiency and the overall process of AM. These capabilities make ANNs a powerful tool for improving AM's performance, which helps in bridging the gap between traditional and modern AM technologies.

3.1. A Basic Overview of ANN: Artificial Neuron

Artificial Neural Networks are special mathematical models that aggregate various units, called neurons, together and process simultaneously their results and finally give an output. This model mimics the human brain, where various neurons receive various signals and, finally, the processing of them takes place inside the neuron body and finally gives a response [9]. Inside a neuron, as shown in Fig. 1, multiple feature input comes in and are multiplied by their corresponding weights and biases, and then an aggregate sum is taken, which is then passed through an activation function for the final answer.

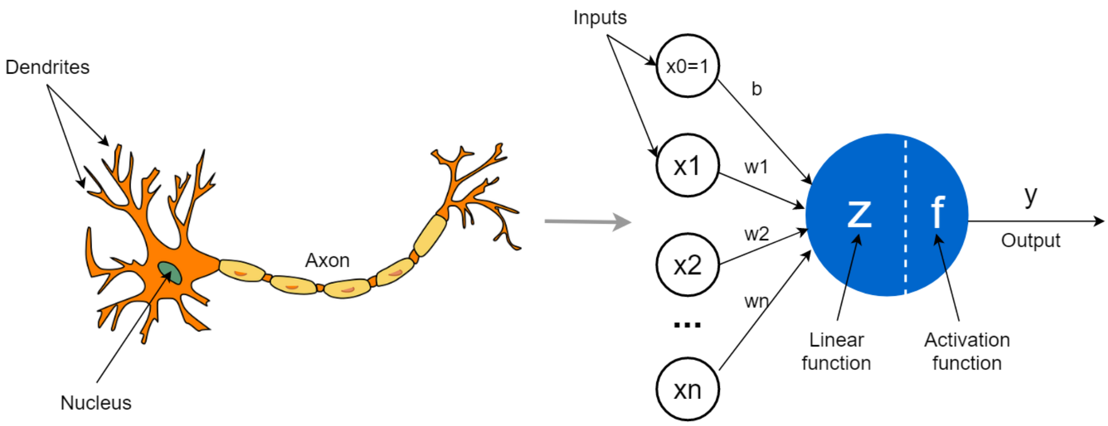


Fig 1. A visual description of a biological and artificial neuron [10].

In a biological neuron, signals are received through dendrites and then processed in the neuron body and transmitted via the axon. In an artificial neuron, multiple weighted inputs are summed along with a bias term and then passed through an activation function, which then further determines the final output. The activation function plays a crucial role in determining the behaviour of the artificial neuron and also the final result [9]. Depending on the problem, it can be a step function, a linear function, or a non-linear function such as the sigmoid function. This simple model can help us analyse various complex data patterns and relations. The mathematical representation is:

$$y(k) = F\,(\sum_{i=0}^{m} w_i(k)\,.\,x_i(k) + b\,)$$

Where

- $x_i(k)$: represents input value,
- $w_i(k)$: denotes the corresponding weights,
- b: Bias term,
- F: is the transfer function, and
- y(k): is the neuron's output

3.2. Neuron Layers

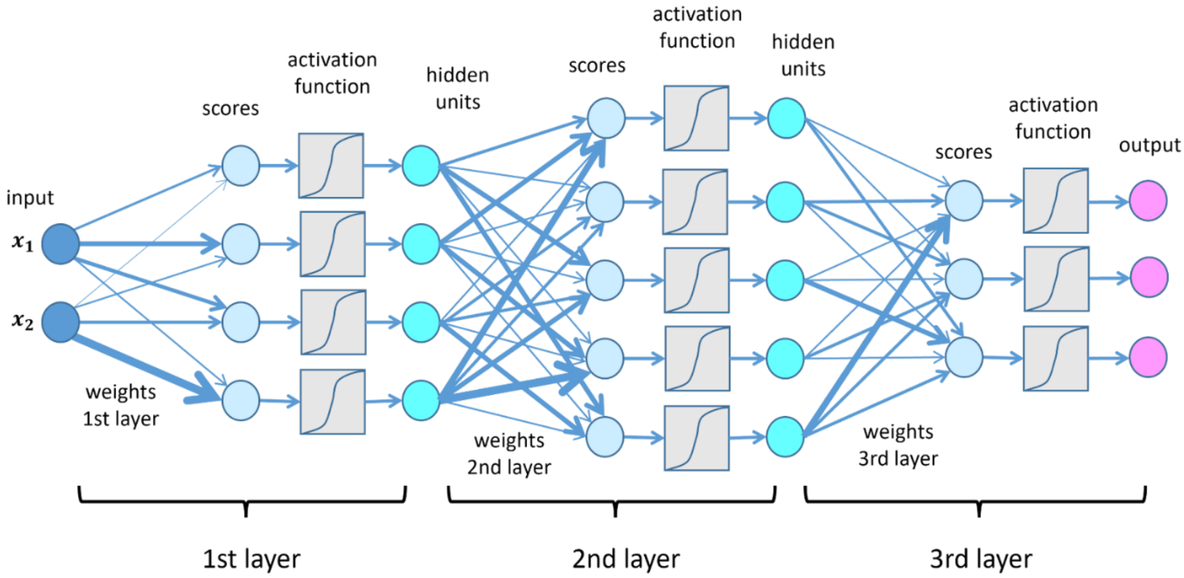


Fig 2. A visual description of all the layers of an ANN.

ANN consists of multiple layers of neurons stacked together in layers. Mathematically, the inputs get processed through these layers, and accordingly, an output is generated based on the weights and biases of the multiple neurons of the multiple layers. The layers of an ANN are mainly classified into three categories: an input layer, a hidden layer, and an output layer. The input layer receives raw data and passes it to the next stage of processing [11]. Then, the intermediate hidden layers perform complex mathematical transformations based on the values of the weights and biases and different activation functions, which also help to introduce a non-linearity to the data. These mathematical transformations help to capture intricate and deep relationships in the data [11]. Finally, all the results of the last hidden layer neurons are then passed to the final output layer, which gives the network's prediction or decision, depending on the type of problem (classification, regression, etc.).

3.3. Loss Function and Gradient Descent

In an Artificial Neural Network (ANN), the main goal is to make accurate predictions from input data. The network is first initialized with random weights and biases, so as a result, its predictions would usually be far from correct. To improve these predictions, the network needs to learn better weight and bias values. This is done by using optimization techniques like gradient descent, which work on a mathematical function called the loss function [11].

The loss function measures how far the predicted outputs are from the actual target values. Common examples include Mean Squared Error (MSE) [12], which is mostly used in regression tasks, and it calculates the average of the squared differences between predicted and actual values. Cross-Entropy Loss, which is commonly used in classification problems, measures how well the predicted probability distribution matches the true labels [13].

For the network to become a better predictor, the loss function must be minimized. This happens through a process called backpropagation, for example, Stochastic Gradient Descent (SGD), which updates weights after each training example. This makes learning faster, but it can be noisy. Adam (Adaptive Moment Estimation), which dynamically adjusts the learning rate for each parameter, often leading to smoother and faster convergence[13].

In backpropagation, the error from the output layer is sent backward through the network, allowing each weight to be adjusted based on its contribution to the error. The optimization itself is carried out using gradient descent, which updates weights and biases step by step in the direction that reduces the loss. The size of each step is controlled by a parameter called the learning rate (η). There are also different versions of gradient descent https://arxiv.org/abs/1609.04747, for example, Stochastic Gradient Descent (SGD), which updates weights after each training example. This makes learning faster, but it can be noisy. Adam (Adaptive Moment Estimation), which dynamically adjusts the learning rate for each parameter, often leading to smoother and faster convergence.https://arxiv.org/abs/1702.05659https://arxiv.org/abs/1702.05659http://sciencedirect.com/science/article/pii/092523129390006O.

$$w = w - \alpha \frac{\partial Loss}{\partial w}$$

3.4 Advanced Neural Networks

Sl No.	Name	Uses	Reference
1	Convolutional Neural Networks (CNNs)	The type of neural network that processes images extracts its features using convolutional layers and then processes further for the corresponding results	[14]
2	Recurrent Neural Networks (RNNs)	This type of neural network is used for processing sequential data like text sequences and time-series data, where a memory is also passed to the forward layers	[15]
3	Long Short-Term Memory (LSTM)	An advanced variant of RNN, which solves the drawbacks of the architecture, like the problems of	[15]

		vanishing gradient and exploding gradient, and also improves the memory retaining functions	
4	Gated Recurrent Unit (GRU)	A simpler alternative to LSTM with fewer parameters	[16]
5	Transformer Networks	State-of-the-art architecture which uses attention mechanisms and a combination of neural networks and normalisation layers for better encoding of sequential data	https://proceedings.neurips.cc/paper/2017/hash/3f5ee243547dee91fbd053c1c4a845aa-Abstract.html
6	Autoencoders	These models use unsupervised learning models that encode data into a compressed representation and are used for dimensionality reduction and anomaly detection.	[17]
7	Generative Adversarial Networks (GANs)	A technique which helps in generating synthetic data with the help of two adversarial neural networks, i.e., generator and discriminator, which compete, and finally the generator generates synthetic data.	[18]

4. Applications of ANNs in AM

ANNs or Machine Learning in general find their application in all three stages of AM - Pre-processing, In-processing, and post-processing phases of AM. For the pre-processing phase of AM, in complex structures that involve more design variables, more interdependencies, and a greater chance of human error, doing the work manually would lead to various errors and may have bad consequences. This is where ML and ANN come into the picture. Deep Learning models can analyse vast datasets, identify non-linear patterns, and predict optimal designs, which gives very good results at the end. Furthermore, ML-based methods (like Generative Adversarial Networks (GANs) and advanced CNNs) can learn from past designs and generate optimized structures [19].

The in-processing phase is where the actual printing happens, making it critical to the final part's quality and performance. During this phase, layers of material are deposited to form the 3D object. However, this process is prone to certain defects, mainly Thermal distortions, Surface roughness, Porosity, and Dimensional inaccuracies [20]. So, having to measure them manually or using traditional methods like Finite Element Methods (FEM), and Computational Fluid Dynamics (CFD)—can be time-consuming and sometimes inaccurate. Here, ANN and ML algorithms can be very helpful. They enable real-time analysis and process optimization by learning from large datasets, which would lead the model to predict the outcomes of parameter changes and further processes. In certain advanced case scenarios, RNNs and Genetic Programming, which will be described in the following section, also help in predicting complex parameters like thermal histories.

The post-processing phase is the final stage before a part is ready for use. Here, mostly defect analysis and surface polishing are carried out to remove surface irregularities, relieving residual stresses. Now, as AM is a layer-by-layer fabrication process, these defects are almost inevitable, which makes the post-processing phase so important. Traditional post-processing methods like grinding, blasting, or manual inspection can be time-consuming and not precise. So, here ML and ANN techniques are used. For Surface Analysis and Polishing, Autoencoders and optical scattering techniques are used to analyse surface data and to work on it further. For Material Properties and Porosity Detection, unsupervised methods like K-means are used to identify voids. In some applications, feature engineering-based **models** are used where they assess how process parameters) influence final product quality.

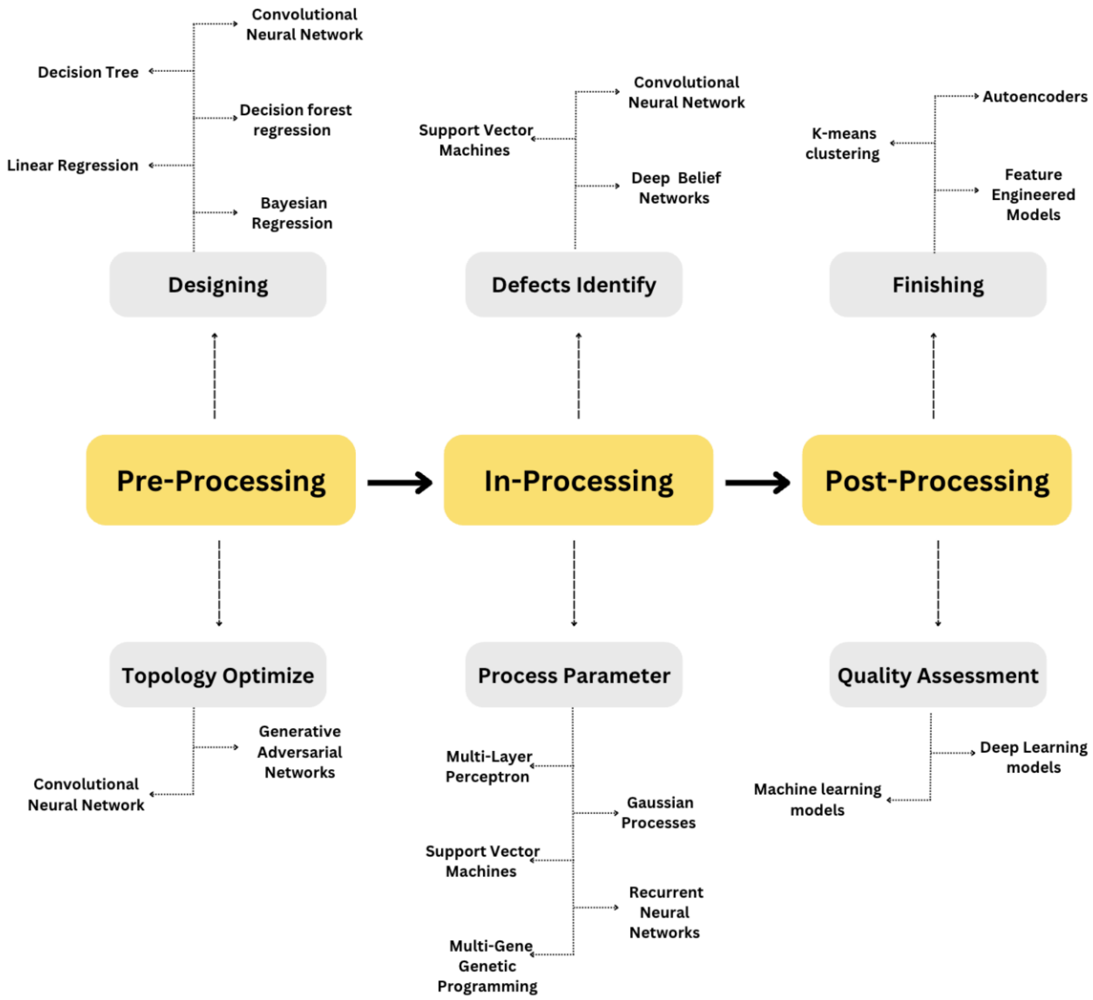


Fig 3. Application of various ML algorithms in Additive Manufacturing

5. Genetic Operators (GAs)

5.1. Types of Operators

Genetic algorithm (GA) is an effective method or strategy for solving combinatorial optimization problems, by taking inspiration from nature. A solution to a particular problem is represented by a

chromosome and is assessed by a fitness function. The process starts with a randomly generated population of chromosomes.
https://pmc.ncbi.nlm.nih.gov/articles/PMC3813526/

Three main operators then evolve the population across generations:

- **Selection**: chooses the fitter chromosomes to pass on.
- **Crossover**: combines pairs of parents to create new offspring, helping to narrow and focus the search.
- **Mutation**: randomly alters genes, introducing diversity and broadening the search.

https://www.researchgate.net/publication/380140694_Appropriate_Combination_of_Crossover_Operator_and_Mutation_Operator_in_Genetic_Algorithms_for_the_Travelling_Salesman_Problem.

5.2. Crossover Operator

These operators are used in exploitation and exploration. Exploitation would refer to already having good solutions and trying to explore them further, and exploration would refer to searching new areas of solutions. https://www.researchgate.net/publication/389748540_Balancing_exploration_and_exploitation_in_genetic_algorithm_optimization_a_novel_selection_operator https://www.sciencedirect.com/science/article/pii/S2210650219302974. The crossover operator does this by creating new offspring by selecting genes from parent chromosomes. The simplest crossover picks a random point, takes the first segment from one parent, and the remainder from the other to form an offspring. https://www.researchgate.net/publication/315175882_Crossover_Operators_in_Genetic_Algorithms_A_Review.

https://www.sciencedirect.com/science/article/pii/S0957417420302050

There are several types of crossover operators such as:

- Single Point Crossover
- N point crossover
- Uniform crossover
- Three parent crossovers
- Arithmetic crossover
- Partially mapped crossover
- Crossover ORDER (OX)
- Cycle Crossover (CX)

5.3. Selection Operator

These operators decide which candidates will reproduce, favouring the fitter ones while reducing the chances of weaker ones, so that the next generation has improved offspring. Elitism is a problem that can arise with traditional selection operators. This is because, while selection is based on finding better individuals, they can weaken the diversity that should also exist in the process.https://joiv.org/index.php/joiv/article/viewFile/3449/1077 This leads to a problem of premature convergence in the mechanism.

https://www.researchgate.net/publication/389748540_Balancing_exploration_and_exploitation_in_genetic_algorithm_optimization_a_novel_selection_operator
. The various types associated with selection operators could be:

- Fitness proportional selection
- Tournament selection
- Linear rank selection
- Exponential rank selection
- Split rank selection
- New tournament selection

5.4. Mutation Operator

These operators are used for the maintenance of the divergence that should exist in the process, which was one of the major issues of traditional selection operators, and hence prevent premature convergence. It generates offspring having entirely differing genes from their parents. The mechanism therefore effectively searches the local search space by random process to disrupt the gene information. https://www.researchgate.net/publication/370441944_Zigzag_mutation_a_new_mutation_operator_to_improve_the_genetic_algorithm . Zigzag mutation operator is an example of a mutation operator.

https://www.sciencedirect.com/science/article/pii/S1226798824003416

5.5. Hybridization of ANN and GA: Approach for AM Optimization

Now that both ANN and GA are discussed, this section will discuss the integration of hybrid ANN-GA or hybridization of ANN and GA, and how its integration results in more optimized results. A trained ANN is used in conjunction with GA to find optimum parameters for the desired process.

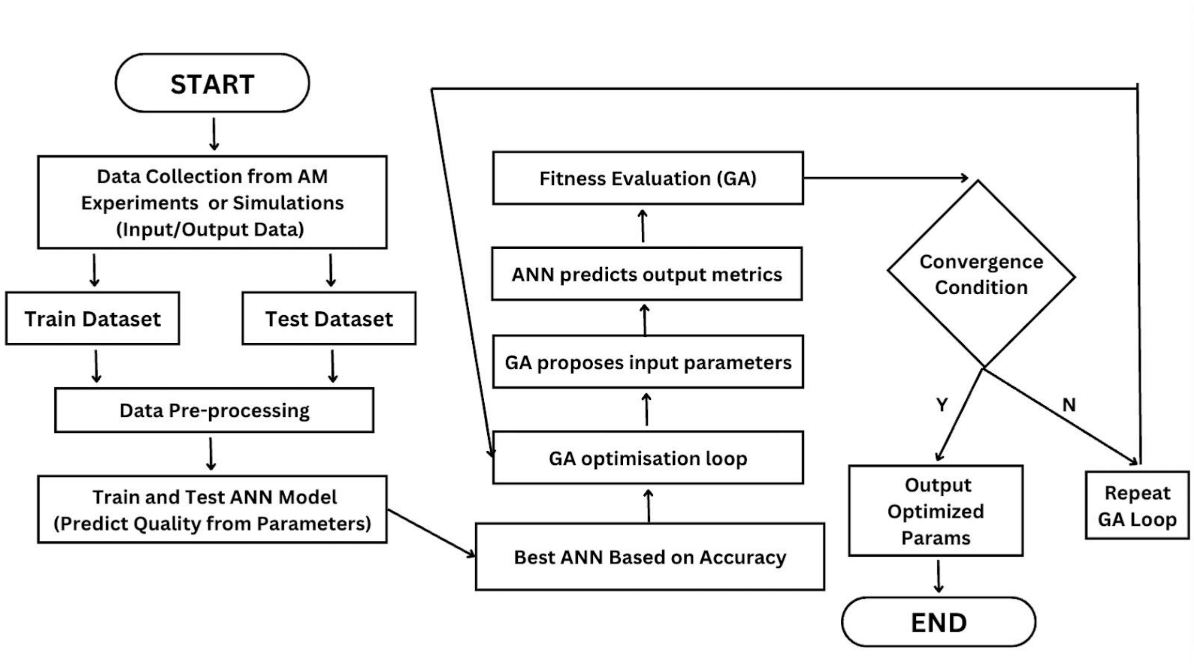
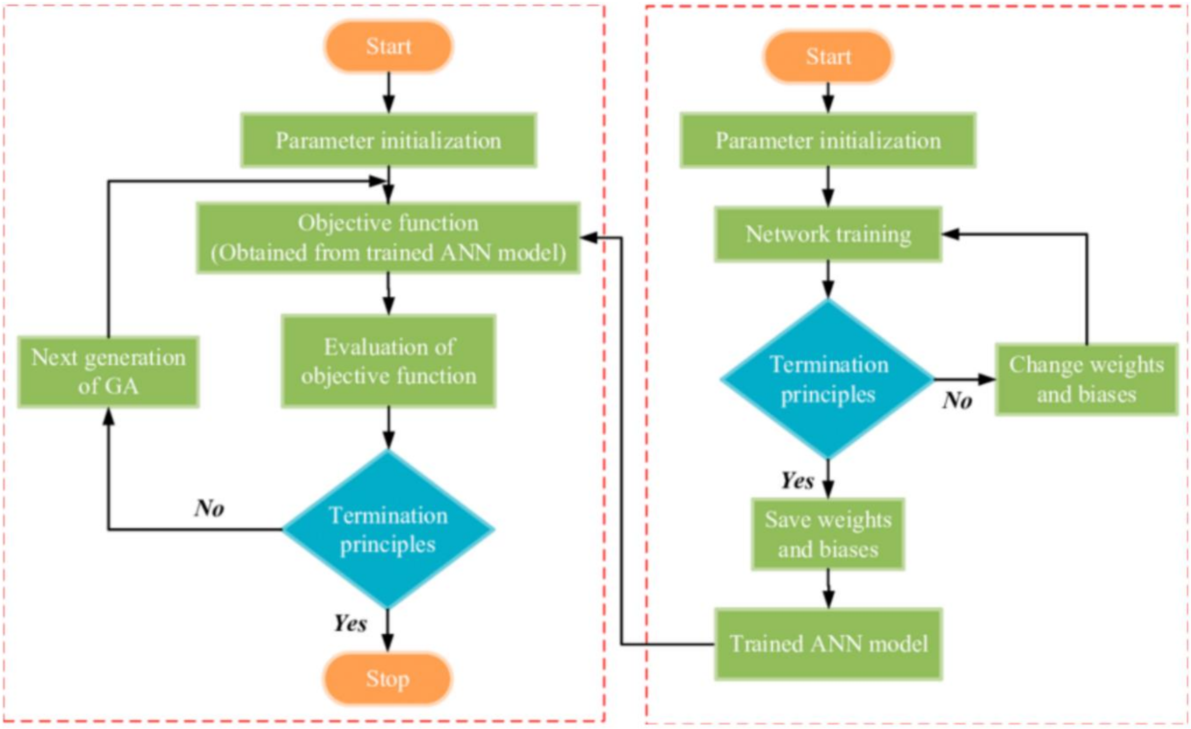


Fig 4. A flowchart depicting a hybrid ANN-GA model [(PDF) A GA-ANN hybrid model for prediction and optimization of CO2 laser-mig hybrid welding process]

In the ANN-GA hybrid model, initially, an ANN model is trained based on the given dataset of input parameters relevant to Additive Manufacturing (AM), such as laser power, scan speed, layer thickness, and hatch spacing, and then corresponding output parameters that include critical quality metrics such as density, surface roughness, tensile strength, microhardness, and residual stress. Using suitable ANN techniques and applying various optimization techniques like Bayesian Regularization, finally helps capture the nonlinear relationships between process parameters and outputs, even in the presence of limited or noisy data. Now our final goal is to find the optimal parameters that would provide the best output.

What GA does is it generates random sets of input parameters and uses the trained ANN to evaluate their corresponding output. These predictions are evaluated using a fitness function (which quantifies how good a solution is). In each iteration, GA refines candidate parameter sets using three main steps: selecting the strongest solutions, exchanging information between them, and introducing small random changes to maintain diversity, leading to the best parameters. This is an iterative process that continues until a convergence criterion is met. This allows for automatic prediction and optimization of key performance metrics in AM processes such as material deposition quality, thermal control, and mechanical properties.

5.6. Implementation of ANN-GA for Additive Manufacturing Process Optimization



The ANN-GA (genetic algorithm) coupled optimization method.

Fig 5. Shows ANN-GA coupled optimisation method

https://www.researchgate.net/publication/338652874_Optimizing_the_Rail_Profile_for_High-Speed_Railways_Based_on_Artificial_Neural_Network_and_Genetic_Algorithm_Coupled_Method

https://www.mdpi.com/1996-1944/17/18/4544

5.6.1. Selection of AM Process Parameters (Temperature, Speed, Layer Thickness, etc.)

Effective process parameter selection is crucial in AM as it directly impacts the formation of defects and the microstructure of printed parts. For Fused Deposition Modeling (FDM), a popular AM process for manufacturing prototypes and functional parts from typical engineering polymers, essential process parameters in FDM prints are strongly shaped by design settings such as layer thickness, toolpath width, deposition angle, and build orientation. Studies on FDM show that tuning these parameters can significantly improve properties like flexural strength, reducing the trial-and-error traditionally needed.
https://pmc.ncbi.nlm.nih.gov/articles/PMC9257345/
https://www.sciencedirect.com/science/article/pii/S2590123024019194?via%3Dihub

In the domain of metal-based additive manufacturing (AM), including its methodological variants like powder bed fusion (PBF), electron beam melting (EBM), direct energy deposition (DED), and wire-arc additive manufacturing (WAAM), the judicious selection of process parameters is of critical significance. These parameters are instrumental in dictating the high heat input and cooling rates, affecting the quality of the produced components. Over the last decade, significant research has been aimed at determining "optimal" processing conditions specific to individual materials to enable defect-free production, mainly involving costly trial-and-error strategies and time-consuming mechanistic simulations.

For Industry 4.0 use, data-driven and automated systems must retrieve the base of expert knowledge for AM and use it in 3D-printed components to eliminate manufacturability problems. Genetic algorithm-based data-driven process selection systems for AM utilize Genetic and Evolutionary Feature Weighting methods optimized using 3D CAD data to choose the best AM method with reference to different requirements and constraints. These systems have been proven to be highly accurate, with two-stage models having an accuracy of up to 97.33% in process selection https://www.oaepublish.com/articles/jmi.2022.18
https://pmc.ncbi.nlm.nih.gov/articles/PMC11433322/

Factor	**Low**	**High**
Temperature (°C)	210	225
Speed	40	90
Infill Direction	0	45
Layer thickness (mm)	0.1	0.3

5.6.2 Data Acquisition and Feature Engineering

Data acquisition and feature engineering are key steps in implementing ANN-GA to optimize the AM process. Quality and quantity of data have direct impacts on the performance of models. Data in AM are collected from experimental trials, simulations, and existing databases.
Transfer Learning (TL) based AM modeling is a recent area that uses data from earlier products to address data paucity in modelling new products. TL finds special applications in AM where data collection is labour-intensive and costly. TL-based model performance is subject to similarity between source and target domains, training data quantity, and data preprocessing methods applied. A case study of metal AM products reported that TL methods combined with decision tree regression (DTR) and ANN outperformed baseline models.
https://onlinelibrary.wiley.com/doi/10.1155/2016/3045254

Instead of using raw sensor data directly, feature engineering extracts meaningful variables such as melt pool width or layer cooling rate that improve ANN predictions, resulting in greater accuracy on unseen new data. Features in AM can be extracted from process parameters, material properties, and part geometry. Feature selection helps to find the model's most relevant variables, decreasing the dimensionality and computational cost. GA has been successfully applied for efficient feature selection to determine the best subset of input variables for ANN.
In data-driven system deployment for AM process choice, effective data handling and feature engineering play a critical role in the model’s performance. Systems utilizing genetic algorithms for feature weighting have shown robust prediction abilities by being capable of handling quantitative feature labelling effectively and enhancing datasets. The method captures the significance of sophisticated data preparation in AM process optimization.
https://pmc.ncbi.nlm.nih.gov/articles/PMC11433322/
https://link.springer.com/article/10.1007/s40430-023-04200-2

5.6.3. Designing the ANN Architecture

Optimal ANN architecture design is critical to successful AM process optimization. The architecture determines the network's capacity to learn complex relationships between inputs (process parameters) and outputs (part quality measures). A hybrid GA method optimizes ANN parameters like weights and biases. The GA seeks the best solution in the search space of the ANN to reduce the discrepancy between model output and training data. The GA is iterated to the desired error level, and implementation is usually adaptable to the problem requirements. https://pmc.ncbi.nlm.nih.gov/articles/PMC7189924/

In TL-based AM modelling, several neural network architectures have been combined with TL methods to increase the performance of models. The TL-based models demonstrate enhanced results, particularly when the similarity between target and source domains dominates, and the best target-to-source training data size ratio is guaranteed.

While developing an ANN architecture for AM process optimization, Key design choices include how deep the network is, how many neurons each layer holds, what activation functions are applied, and how fast the model updates weights during training. These parameters strongly impact the model's performance and, therefore, need to be appropriately chosen based on the particular requirements of the AM process to be optimized. Architecture development can also be determined by the nature of process parameters to be optimized and the quality characteristics to be optimized.
.https://arxiv.org/pdf/2305.11181.pdf

5.6.4. Using GA for Weight Optimization vs Hyperparameter Tuning

Genetic Algorithms can be applied to an ANN in two general ways: optimizing the neural network's weights and biases and optimizing the network's hyperparameters. Both can provide different benefits to optimizing the AM process.

In weight optimization, GA determines the best weights and biases for the neural network, which is very helpful when gradient-based techniques normally employed to train neural networks get trapped in local minima. The hybrid ANN-GA methodology offers a search space in which GA adjusts the weights and biases to obtain lower error rates. Model output to training data error is minimized by repetition of GA until a target threshold is reached, essentially covering a more extensive solution space than conventional methods.
https://pmc.ncbi.nlm.nih.gov/articles/PMC7189924/

GA finds the best architecture and learning parameters for hyperparameter optimization, such as the number of layers, neurons per layer, activation functions, learning rate, and other structural parameters. The hybrid and genetic algorithms of PSO-ANN have successfully predicted and optimized manufacturing attributes such as roughness, cost, and energy consumption, where the genetic algorithm found optimal parameters resulting in better outcomes by a considerable margin.

The decision to optimize hyperparameters or weights depends on several parameters, such as the problem complexity, the computational power available, and the requirements of the AM process. In certain implementations, the best suitable option can be a sequential or an integrated method where GA determines the optimal network structure first and optimizes the weights of the architecture second.
https://pmc.ncbi.nlm.nih.gov/articles/PMC7189924/
https://www.nature.com/articles/s41598-024-83029-8

5.6.5. Training and Validation Process

The training and validation step is the most essential part of employing ANN-GA to optimize the AM process so that the model can accurately predict process parameters and part quality metric relationships and generalize to new, unseen data.

The ANN acquires patterns and relationships by varying weights and biases while training. When GA is used to optimize weights, the training process evolves a series of candidate solutions (weights and biases) through multiple generations. Each solution is evaluated based on a fitness function, typically the error between predicted and actual outputs. During training, only the best-performing candidate solutions are carried forward and recombined, gradually improving results across generations until the error falls within an acceptable range or a maximum number of generations is reached.
https://www.nature.com/articles/s41598-024-83029-8
https://www.mdpi.com/1996-1944/17/18/4544

A PSO-ANN hybrid algorithm based on a genetic algorithm has been demonstrated to produce high correlation values of actual and predicted outputs, i.e., 0.97%. The genetic algorithm optimized cutting parameters (Vc = 25.45 m/min, f = 0.111 mm/rev, and ap = 0.58 mm), and the resulting notable improvements in results obtained validated the capability of the hybrid approach to describe intricate data relationships.
https://onlinelibrary.wiley.com/doi/10.1155/2016/3045254
https://www.tandfonline.com/doi/abs/10.1080/21681015.2023.2243312

Validation tests the trained model on unseen independent data, checking for generalization capacity and potentially unmasking defects such as overfitting. In data-driven process selection systems for AM via genetic algorithms, two-stage models have increasingly realized higher accuracies, with the first-stage models realizing around 70% accuracy and the second-stage models realizing up to 97.33%. High accuracies attest to the efficiency of ANN-GA hybrid techniques in optimizing AM processes.
The validation process offers insights for model enhancement by allowing model adjustments to architectural design, training procedures, or feature engineering procedures to enhance performance outcomes. Cross-validation protocols are frequently used to verify that the model is stable in performance across several data subsets, hence offering a more consistent measure of the model's capacity to optimize additive manufacturing processes.
https://pmc.ncbi.nlm.nih.gov/articles/PMC11433322/

5.7. NeuroGenetic Optimization: Evolutionary Fine-Tuning of Neural Networks for Manufacturing Quality Prediction

The primary objective is to develop an optimal neural network model that accurately predicts manufacturing quality ratings based on process parameters. The genetic algorithm is employed to find the best hyperparameter configuration for the neural network, maximizing prediction accuracy while minimizing error.

5.7.1. Dataset Description

The project uses a manufacturing dataset (manufacturing.csv) that contains process parameters and quality metrics for a manufacturing process. The dataset includes the following features:

- Temperature (°C)
- Pressure (kPa)
- Temperature x Pressure (derived feature)
- Material Fusion Metric
- Material Transformation Metric
- Quality Rating (target variable)

Here are some sample rows from the dataset:

Temperature (°C)	Pressure (kPa)	Temperature × Pressure	Material Fusion Metric	Material Transformation Metric	Quality Rating
209.7627008	8.050855372	1688.769167	44522.21707	9229575.96	99.99997052
243.0378733	15.81206837	3842.931469	63020.765	14355367.16	99.98570341
220.5526752	7.843130045	1729.823314	49125.95025	10728388.69	99.99975761
208.9766366	23.78608919	4970.736918	57128.88155	9125701.954	99.99994784
184.7309599	15.79781221	2918.345014	38068.20128	6303791.886	99.99999986
229.1788226	8.498306097	1947.631786	53136.69065	12037071.66	99.99878571
187.5174423	19.41285094	3640.248155	42478.6945	6593259.8	99.99999973
278.3546002	7.070943886	1968.229758	77834.81823	21567221.67	95.73272258
292.7325521	20.4328958	5981.373734	94223.14707	25084521.95	64.62359688

The Quality Rating ranges from approximately 4 to 100, with higher values indicating better quality. The dataset shows a clear relationship between process parameters and quality, with specific temperature and pressure combinations yielding optimal quality ratings.

5.7.2. Methodology

In this section, a demonstration of how the neural network architecture is dynamically optimized using a Genetic Algorithm (GA) is shown. The design space incorporates a wide variety of structural, training, and regularization parameters, enabling an extensive exploration of possible architectures.

The hyperparameter search space is summarized below:

Parameter	Range / Options
Number of hidden layers	1 – 4
Neurons per layer	1 – 20 (layer-dependent)
Batch size	10, 25, 50, 100, 200
Optimizers	Adam, Adagrad, RMSprop, SGD
Kernel initializers	Uniform, Normal
Epochs	50, 100, 150, 200
Dropout rate	0, 0.1, 0.2, 0.3, 0.4, 0.5
Training data percentage	5%, 10%, 15%, 20%, 25%, 30%
Activation functions	ReLU, tanh, sigmoid, ELU

For genetic algorithm, parameters are summarized as follows: -

Parameter	Value
Number of generations	12
Population size	40
Number of parents for mating	8
Mutation percentage	30%

The fitness function is a composite metric that balances training and validation performance:

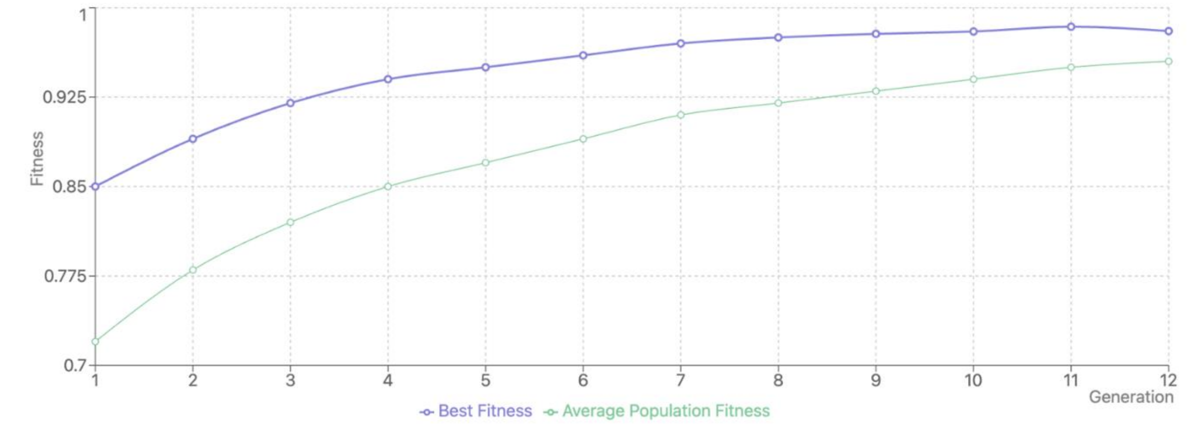
- Objective = (1-RMSE) * 0.5 + (1-RMSE_val) * 0.5

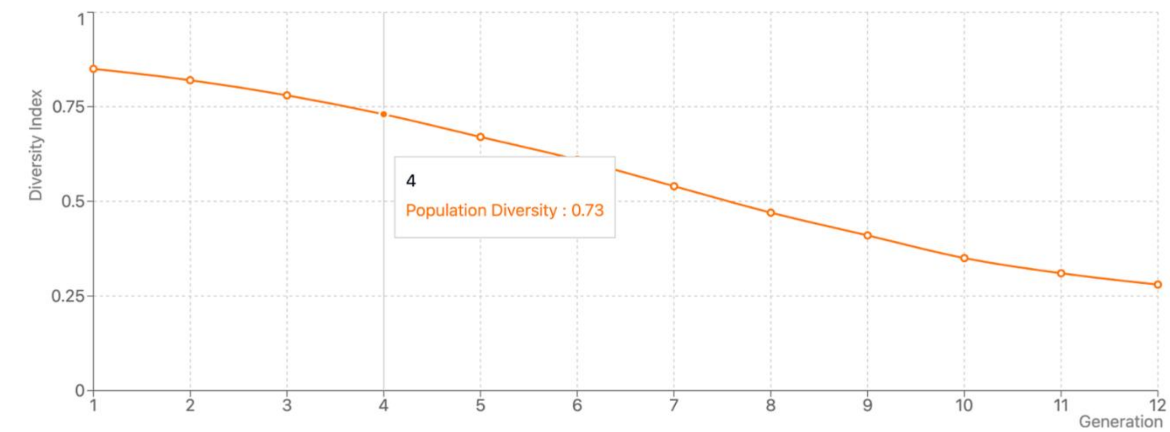
Additional metrics tracked include MAE, validation MAE, R^2, and validation R^2.

5.7.3. Results

Convergence Plot (12 Generations)

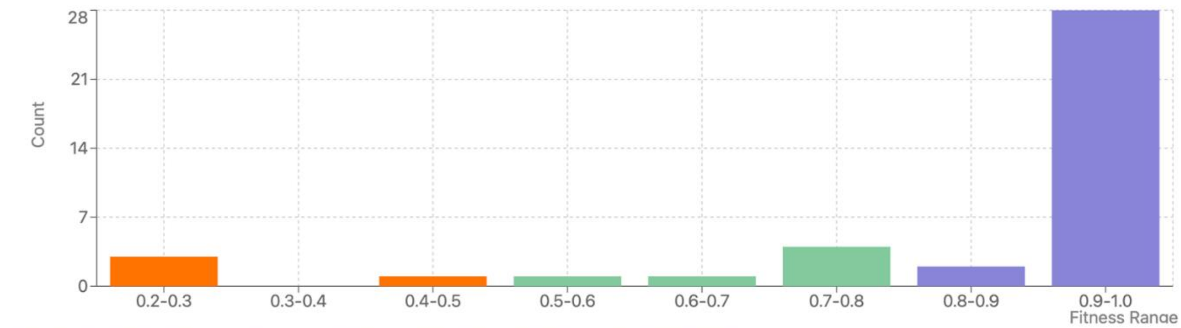
This plot shows how the genetic algorithm optimization improved the neural network performance over generations.





The decreasing diversity indicates genetic algorithm convergence, as the population becomes dominated by high-performing individuals.

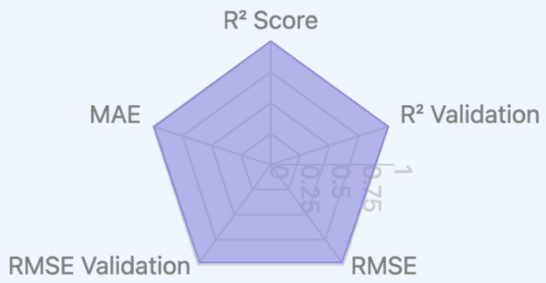
Final Population Fitness Distribution



Most individuals in the final population have high fitness scores (0.9-1.0), indicating successful optimization.

Final Best Model Performance:

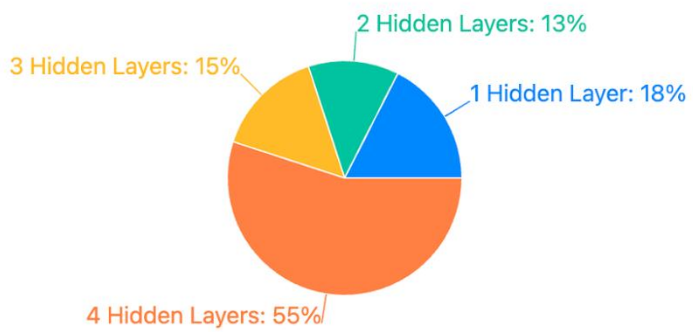
- RMSE: 0.02
- Validation RMSE: 0.02
- R^2: 1.00
- Validation R^2: 1.00
- MAE: 0.01
- Objective Function: 0.9803578257135771



Parameter Distribution in Final Population

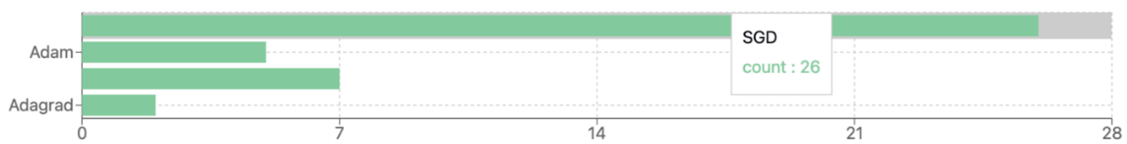
These charts show the distribution of key hyperparameters in the final generation.

Neural Network Architecture

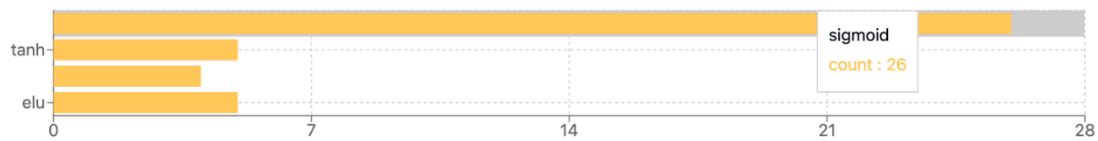


4-layer architectures dominate the final population (55%), suggesting deeper networks perform better for this task.

Optimizer Distribution



Activation Function Distribution



Best Model Configuration:

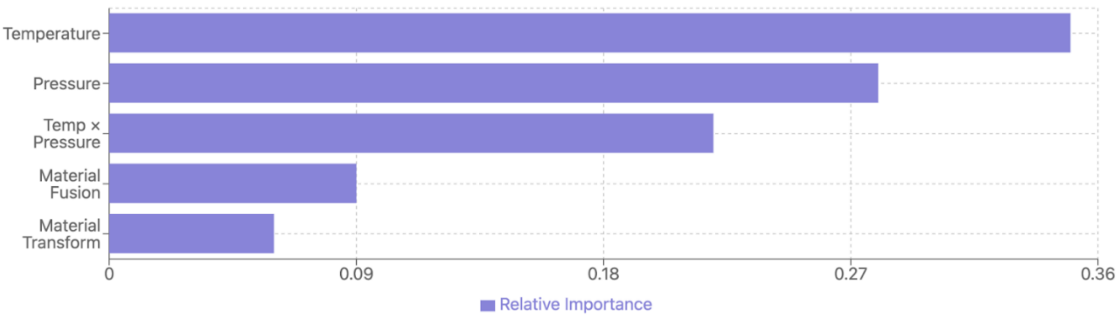
```
[4, (10, 13, 14, 3), 10, 'sgd', 'normal', 200, 0, 0.25, 'sigmoid']
```

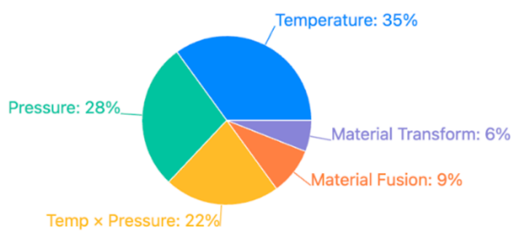
- 4 hidden layers with (10, 13, 14, 3) neurons
- Batch size: 10
- Optimizer: SGD
- Kernel initializer: normal

- Epochs: 200
- Dropout: 0
- Training data percentage: 25%
- Activation function: sigmoid

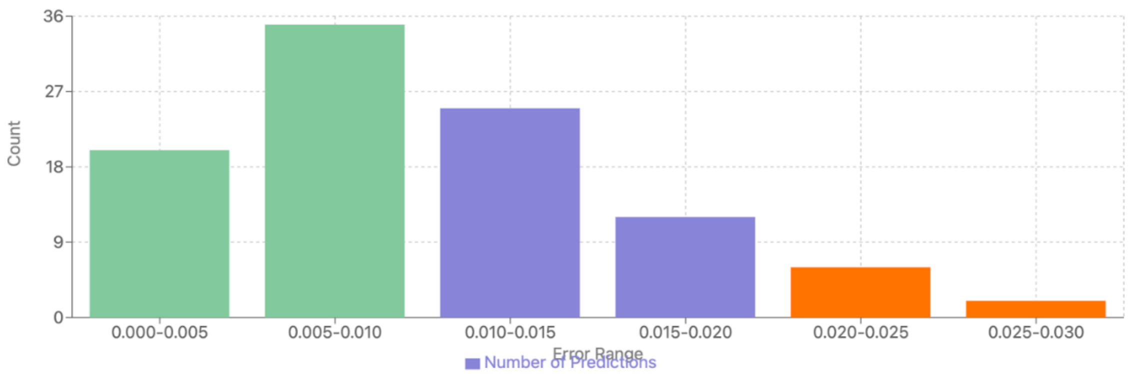
Feature Importance Analysis

Relative importance of input features in predicting manufacturing quality.

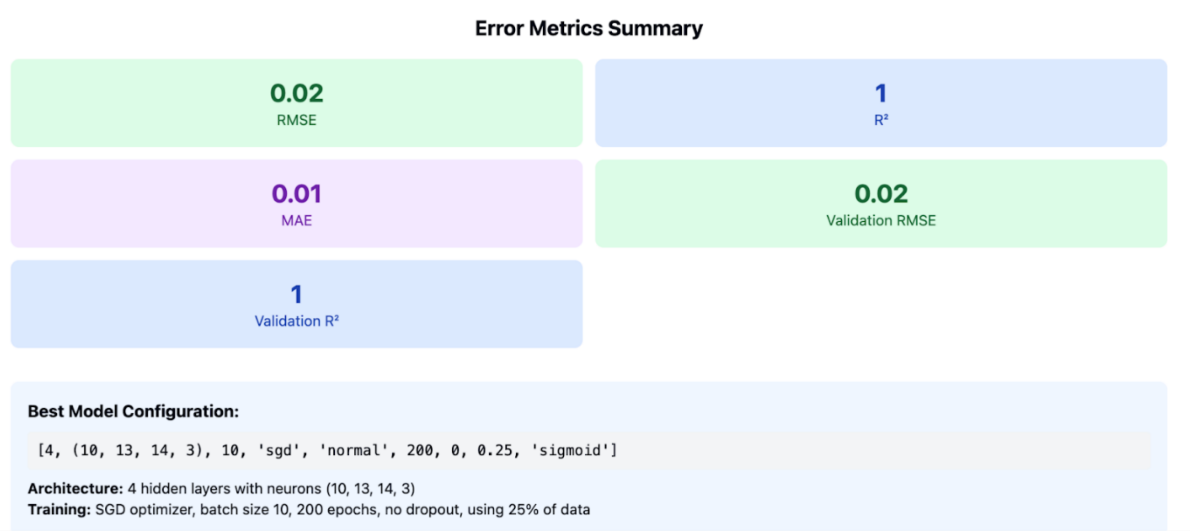


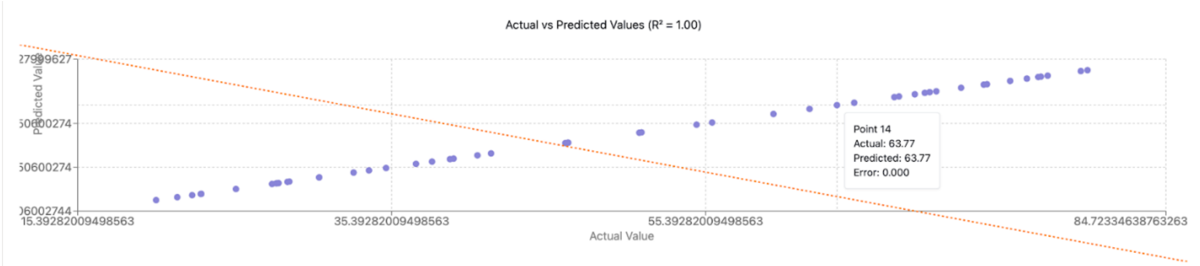


Distribution of prediction errors in the best genetic algorithm model (RMSE: 0.02)



Most predictions have errors below 0.015, with the highest concentration in the 0.005-0.010 range, demonstrating the genetic algorithm's success in optimizing the neural network.





Points closely follow the ideal y=x line, demonstrating the model's extremely high accuracy. The genetic algorithm has optimized the neural network to achieve near-perfect predictions.

6. Advantages, Limitations, and Challenges

6.1. Benefits of hybrid ANN-GA in additive manufacturing

Additive manufacturing (AM) is transforming how complex 3D objects are made, but it still lacks clear, automated design rules for different processes. Choosing the right AM process for a specific part often requires expert knowledge, which can be hard to replicate. To address this, researchers have proposed GA-based frameworks that automatically suggest the most suitable AM process based on design requirements. By analysing 3D CAD models, the system uses optimized feature weighting to match design requirements with the most appropriate AM techniques. The steady-state genetic algorithm (SSGA) outperformed other methods like estimation of distribution and particle swarm optimization. This shows that genetic algorithms are crucial in improving decision-making in AM, enabling accurate, automated process selection and supporting the broader goals of Industry 4.0 [2].

https://www.mdpi.com/2075-1702/13/9/813

The application of Genetic Algorithms (GA) in Additive Manufacturing (AM) has proven to be highly effective for optimizing the fabrication process. In the discussed study, GA was used to establish a multi-objective optimization framework aimed at improving build rate, dimensional accuracy, and surface finish of parts produced by the Fused Deposition Modelling (FDM) technique. By simulating the evolutionary principles of natural selection, GA iteratively searched for the best combination of input parameters—such as layer thickness, orientation angle, raster angle, raster width, and air gap—that influence the final quality of AM parts. The approach facilitated a comprehensive exploration of the solution space and identified optimal parameter sets that balance trade-offs between conflicting objectives. Such optimization approaches have been shown to improve both product quality and manufacturing throughput, proving effective in handling the nonlinear nature of AM parameter interactions

https://www.researchgate.net/publication/379455258_Genetic_Algorithm-Based_Framework_for_Optimization_of_Laser_Beam_Path_in_Additive_Manufacturing.

Genetic algorithms (GAs) have proven to be effective tools in optimizing scheduling problems in additive manufacturing (AM) due to their ability to handle complex, multi-objective, and dynamic constraints. In AM, efficient scheduling is crucial for minimizing production time, reducing resource conflicts, and improving overall system throughput. GAs simulates the process of natural evolution by employing selection, crossover, and mutation operators to iteratively improve a population of schedules. When applied to AM, these algorithms can consider multiple criteria such as part priority, machine availability, and production deadlines. By optimizing job sequencing and machine assignment, GAs help in enhancing productivity and flexibility in AM environments, making them suitable for both single and multiple machine scheduling scenarios https://www.researchgate.net/publication/379455258_Genetic_Algorithm-Based_Framework_for_Optimization_of_Laser_Beam_Path_in_Additive_Manufacturing.

6.2. Challenges associated with the method

A major drawback of applying GA in AM is the heavy computational load and energy demand caused by repeated evaluations over many generations. Since GA involves iterative processes with multiple generations, crossover, mutation, and fitness evaluations, it demands significant computational power. This leads to higher energy usage, especially when optimizing complex multi-objective problems such as minimizing production time and energy or maximizing surface quality and strength. In industrial settings where time and energy efficiency are crucial, such resource-intensive optimization can be a bottleneck.

Another challenge is the difficulty in accurately modelling and handling dynamic constraints inherent to additive manufacturing processes. These constraints can include machine limitations, thermal stresses, material behaviour, and process-induced defects. Traditional GA frameworks may struggle to incorporate these rapidly changing or non-linear constraints effectively. As a result, the optimized solutions may not always be practically implementable or may lead to suboptimal performance during actual production, reducing the effectiveness of the algorithm.

https://journals.sagepub.com/doi/10.1177/1687814018822880

6.3. Strategies to overcome these challenges

To address the high computational and energy costs associated with GA in additive manufacturing, one effective strategy is to integrate hybrid optimization frameworks. For example, combining GA with other techniques such as fuzzy logic or neural networks can reduce the number of generations required for convergence by intelligently guiding the search process. Additionally, parallel processing and distributed computing can be used to speed up computation, thereby reducing overall energy consumption and making the process more scalable for industrial use.

Regarding the challenge of managing complex constraints in AM, modifying the genetic algorithm structure to include domain-specific knowledge and adaptive operators proves useful. This can include integrating process simulation data, adaptive mutation rates, or constraint handling strategies directly into the fitness function. Such customizations help ensure that the solutions generated by GA are not only optimal in theory but also feasible and effective when applied to real-world additive manufacturing setups. These improvements can make GA-based optimization more robust and aligned with practical manufacturing constraints.

https://link.springer.com/article/10.1007/s40430-023-04200-2

7. Future Trends in AI-Driven Additive Manufacturing

7.1. Integration with Reinforcement Learning and Other AI Techniques

Recent research demonstrates the transformative potential of integrating reinforcement learning (RL) with ANN-GA frameworks to enable adaptive, real-time control in AM processes. A 2025 study [https://www.tandfonline.com/doi/full/10.1080/01605682.2025.2475021?src=] introduced an RL-enforced adaptive large neighbourhood search (ALNS) algorithm to synchronize production and delivery in AM supply chains. By using proximal policy optimization (PPO), the hybrid RL-ALNS framework reduced total service time by 28% compared to traditional heuristics, proving critical for localized AM ecosystems requiring rapid iteration. In metal AM, RL agents dynamically adjust laser power and scan velocity during wire-arc additive manufacturing (WAAM), reducing spatter formation by 63% through microsecond-level parameter tuning [https://arxiv.org/html/2409.00877v1]. Emerging hybrid architectures combine RL with:

- Generative Adversarial Networks (GANs): Synthesizing synthetic defect data to train ANNs for rare failure scenarios, reducing physical trials by 40% [https://arxiv.org/html/2409.00877v1].
- Physics-Informed Neural Networks (PINNs): Integrating thermal gradient equations into ANN models to predict melt pool stability in laser powder bed fusion (LPBF) with 94% accuracy [https://www.nature.com/articles/s41598-024-80541-9].

These systems address challenges like partial observability in layer-wise processes, where subsurface defects remain undetectable by conventional sensors. Hierarchical RL frameworks decompose tasks into subgoals (e.g., porosity minimization before surface optimization), achieving multi-objective efficiency gains [https://www.nature.com/articles/s41598-024-80541-9].

7.2 Real-Time Optimization with Digital Twins

Digital twins (DTs) are revolutionizing AM by enabling virtual-physical synchronization through IoT sensors and ANN-GA models. A systematic review [21] highlights key implementations:

1. Process DTs: Monitor thermal gradients and material flow in real time, adjusting laser power within 100 µs to stabilize melt pool depth (50–300 µm) during DMLS.

2. Product DTs: Predict distortion fields in wire-arc AM using a hybrid VQVAE-GAN and RNN model, reducing root mean square error (RMSE) to <0.9 mm—143% lower than finite element methods.

The NIST AI2AM initiative employs DTs to simulate 10^6 process iterations hourly, enabling in situ defect correction. For example, residual stress mitigation in aerospace components is achieved by combining reduced-order thermal models with GA-optimized support structures, cutting qualification times from 12 months to 8 weeks [22]. Challenges persist in scaling DTs across multi-vendor ecosystems, necessitating standards like ISO/ASTM 52926 for interoperability [21].

7.3. AI-Driven Predictive Maintenance

ANN-GA systems are advancing predictive maintenance in AM equipment:

- Laser Degradation Prediction: ANNs trained on photodiode data forecast fibre laser efficiency drops 40 hours before failure, reducing unplanned downtime by 30% [22].
- Nozzle Clog Detection: CNNs analyse melt flow imagery in FDM systems, triggering GA-optimized purge cycles when partial blockages are detected [21, 23].

A 2024 framework integrates sensor fusion (coaxial cameras, infrared thermography) with physics-based neural networks to predict keyhole pores and cracks in LPBF [24]. This system achieved 93.4% defect compensation in WAAM by auto-tuning robot toolpaths, though post-processing milling remains necessary for precision surfaces [21].

7.4. Potential Industry Applications

Industry	Application	Details
Aerospace	ANN-GA Hybrid for Distributed AM Networks	Georgia Tech's secure supply chain models use ANN-GA systems to optimize AM networks, reducing lead times by **35%** for titanium aerospace brackets.
	Digital Twins (DTs) for Compliance	DTs simulate cryogenic cycling effects on **Inconel 718** components to ensure **FAA compliance** for fatigue life.
Biomedical	ANN-based Topology Optimization	ANN-driven designs for **patient-specific cranial implants** use graded lattice structures to reduce **stress shielding** by mimicking bone stiffness.
	GA-optimized Build Orientation	Genetic Algorithms optimize build orientation, cutting **post-processing time by 65%**.
Automotive	ANN-guided Resin-Fiber Infusion	Reinforce 3D's **Continuous Fiber Injection Process (CFIP)** uses ANN-guided infusion to strengthen **FDM-printed aluminium brackets**, increasing **tensile strength by 40%**.
	GA-optimized Material Usage	Reinforce 3D's **Continuous Fiber Injection Process (CFIP)** uses ANN-guided infusion to strengthen **FDM-printed aluminium brackets**, increasing **tensile strength by 40%**.
Energy	PINN and DT Integration	Digital Twins combined with Physics-Informed Neural Networks (PINNs) predict thermal profiles in DED turbine blades
	RL-driven Defect Localization	Reinforcement Learning (RL) enhances defect localization, **extending service life by 3–5 years**.

8. Summary

Implementing ANN-GA hybrid approaches for additive manufacturing process optimization offers a powerful framework for addressing the complex challenges associated with parameter selection and quality control. By leveraging the pattern recognition capabilities of neural networks with the global optimization strengths of genetic algorithms, manufacturers can develop highly accurate predictive models that adapt to the unique requirements of different AM processes. The systematic approach outlined in this chapter—from parameter selection and data acquisition to architecture design and validation—provides a comprehensive methodology for implementing these hybrid systems in practical manufacturing environments.

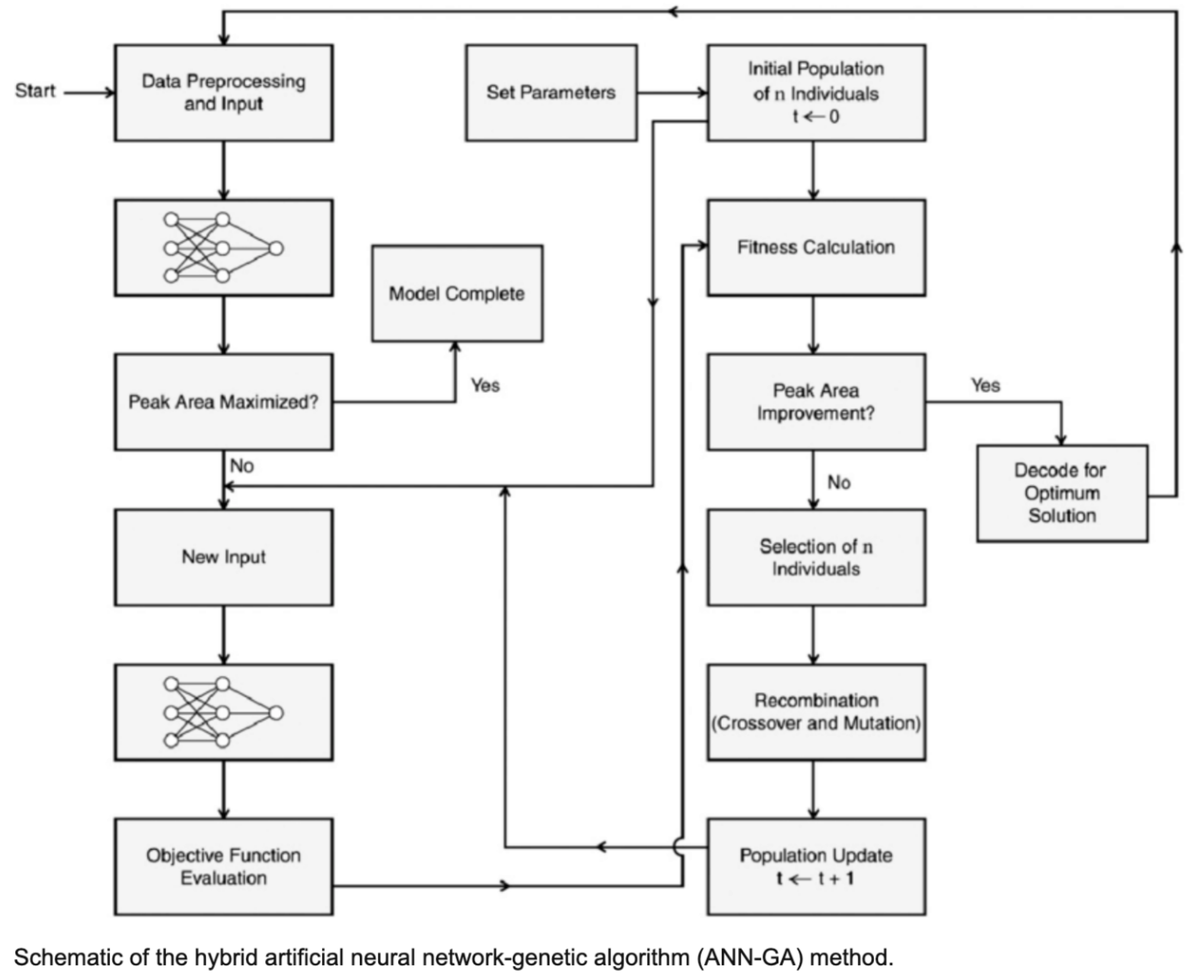


Fig 6. Schematic of the hybrid ANN-GA method [25]

Optimization method selection depends on problem dimension, number of objectives, and computational tractability:

1. Grid search is appropriate for low-dimensional spaces with well-defined parameter limits, like initial layer thickness effects research.
2. Bayesian optimization prevails over high-dimensional continuous parameter tuning problems (e.g., laser power gradients) where sample efficiency becomes essential.
3. GAs perform best in multi-objective AM problems, such as mechanical properties versus cost balancing, through their ability to explore disjoint regions of the search space [26].

Recent benchmarking of AM builds orientation optimization using Cuckoo Search Algorithm (CSA) and particle swarm optimization against GA indicated that although cuckoo search and particle swarm optimization optimized better in some metrics than GA, the flexibility and adaptability of GA to ANN architectures make it a strong contender for hybrid architectures. Hybrid approaches, e.g., using Bayesian optimization for initial hyperparameter screening followed by GA-based weight tuning, would complement the strengths of both approaches.

In brief, no optimization method outperforms the others for ANN-GA applications to AM. Practitioners must ensure the choice of method is accompanied by problem-specific constraints, with Bayesian optimization being the choice for the efficiency of hyperparameter tuning and GAs for multi-objective or weight optimization problems [27].

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