MACHINE LEARNING IN ADDITIVE MANUFACTURING AS ENABLER FOR SMART SUSTAINABLE MANUFACTURING: A REVIEW

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ABSTRACT

Machine learning (ML) is becoming an increasingly popular concept since its main goal is to optimize systems by allowing one to make smarter and effective use of materials, products and services. In the manufacturing industry machine learning can lead to increased quality, lead time reduction, minimized cost, etc. It simultaneously enables systems to be designed for managing human behaviour. This study used a systematic review to investigate the different ML algorithms applied to additive manufacturing within the sustainable manufacturing context. The findings include different ML techniques which have been applied to additive manufacturing processes and ML trends in these processes.

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1. INTRODUCTION

Additive manufacturing (AM) processes are processes which utilize technologies to build physical 3D objects directly from computer-aided design (CAD) data, by adding thin layers of material on top of each other to create the final product [1], without tooling or human intervention [2]. The material which can be used, include plastic, metal and concrete. The material is used in various forms, including liquid, power, sheet or wire [3]. Additive manufacturing produces high quality 3D products with complex geometries in minimum lead time [4]. Additive manufacturing is also known as rapid prototyping [5].

Machine learning algorithms are becoming increasingly popular and have been applied to a variety of additive manufacturing processes to reduce building time and to increase quality. Quality within the AM industry include improved surface finish, minimized support structures, increased structural strength, increased stiffness, reduced warp deformation, increased dimensional accuracy, etc. The paper focuses on machine learning applications in additive manufacturing. Firstly, the methodology is discussed followed by machine learning techniques and their applications in the industry.

2. METHODOLOGY

2.1 Systematic review

The research methodology used for this study is the systematic review. The systematic review enables the growth of a knowledge base consisting of relevant and useful information, generates information based on research conducted in the areas of study which are of interest and identifies opportunities for further investigation [6]. A systematic review makes use of a pre-specified criteria to collect, evaluate and summarize the collected empirical evidence and research to answer a well-defined research question.

The research question for this study is: what are the different ML algorithms which have been applied to AM and what are the trends in these applications.

The focus of this paper is to review the different machine learning techniques which have been applied in the additive manufacturing industry, in terms of quality assurance, optimized processes, etc. The literature review covers full papers from 2000 to 2018 which are selected according to the criteria provided in Table 1. The template was created by [7] and modifications were added by the author.

Table 1: The selection criteria for the literature.

Criteria	*Desired value*
Industrial sector of the application	Manufacturing
Specific process	Additive manufacturing
Purpose of the study	Scheduling, process chains, quality assurance
Keywords	Machine learning, artificial intelligence, optimization, additive manufacturing, rapid prototyping, layer manufacturing, 3D printing, design, quality, scheduling, sequencing
Date of publication	January 2000 – April 2018

Every paper was further analyzed and the following data about each was extracted: title of the paper, year published, the specific additive manufacturing process (ex. fused deposition modelling), the purpose of the study (scheduling, process chains, quality assurance), the machine learning algorithm(s) used, input variables and output variables. This data is used to fulfil the objectives of the study.

In the following section the results and findings of the literature review is presented.

3. FINDINGS

3.1 Machine learning techniques

A variety of machine learning techniques have been applied in the research. The most popular methods include neural networks (NNs), genetic algorithm (GA), regression modelling, response surface methodology (RSM), and fuzzy inference systems (FIS). Less common methods include support vector machines (SVMs), simulated annealing (SA), finite element analysis (FEM) [8], etc. Hybrid or combinations of machine learning techniques have also been applied.

3.1.1 Neural networks

A neural network (NN) or artificial neural network (ANN) is an arrangement of statistical algorithms which structure is based on the biological brain patterns found in human brains. NNs are used to identify and create the non-linear mathematical relationships between input variables and the output variable(s). NNs are applied to classification, estimation, simulation and prediction problems [1].

A NN is an interconnected parallel network consisting of 3 or more parallel layers: input layer, hidden layer(s) and output layer. Each layer consists of parallel neurons, which uses weights, biases and transfer or activation functions to create a model which best describe the non-linear relationship between the input and output variables. The input layer has a number of neurons equal to the number of input variables and the same holds for the output layer and output variables. The transfer functions (also called neuron functions) are mathematical functions and examples include sigmoid-logistic [9], linear [10], tangent-sigmoidal [11] [12], hyperbolic trigonometry, exponential [1] and Gaussian [13] activation functions. Figure 1 shows the structure of a basic NN. Network parameters include the number of training and testing data, learning rate, number of hidden layers and neuron function used and they have an effect on the accuracy, reliability, effectiveness and computational load of the neural network [1]. A variety of NNs are available, including back propagation NN (BPNN), feed-forward NN (FFNN) or multi-layer perceptrons, general regression NN (GRNN) [13], recurrent NN (RNN) and radial basis function NN (RBFNN). The self-organization feature map (SOP) [14] is a variant of a NN. With some NNs, including back-propagation NN (BPNN) and recurrent NN (LRNN), the output or part of the output of the hidden layer is fed into to hidden layer as input, thus creating a feedback loop.

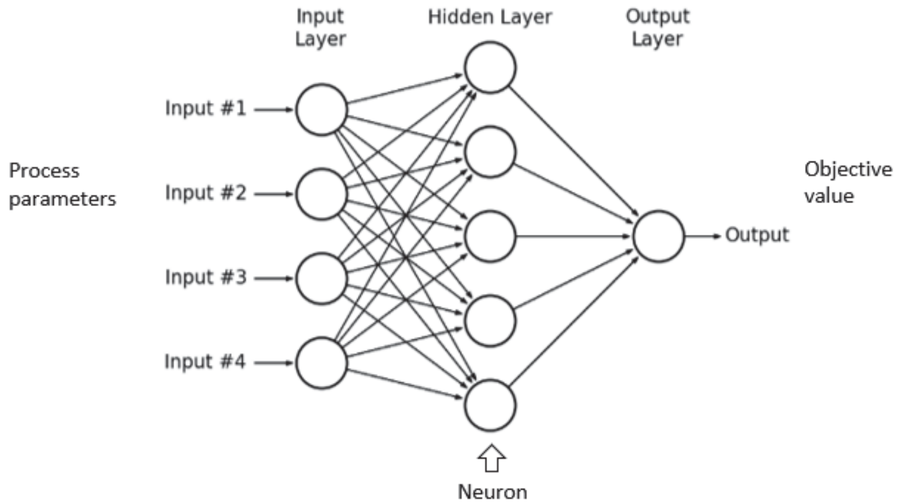

Figure 1. A basic feed-forward neural network.

To develop and apply a neural network, three sequential processes occur: training, validation and testing. The neural network must be trained to determine the most applicable weights and biases to model the non-linear input-output relationships. The training includes multiple simulations of the NN consisting of different combinations of the number of neurons in the hidden layer and the number of delays in the feedback. Various training algorithms exist including the Bayesian regulation [11], Levenberg–Marquardt algorithm [12], resilient gradient descent [10], Conjugate Gradient Descent (CGD), and Bayesian Inference (BI). Next, the neural network is validated using validation data to determine whether it models the non-linear relationship between the variables accurately or within acceptable limits. Usually minimized error is used to validate the NN. Different statistical measures are used to determine the error of the net, for example Mean Absolute Percentage Error (MAPE), mean square error (MSE), root mean square error (RMSE), Regression value or coefficient of determination (R or R^2), multi-objective error function (MO) [9] and maximum/average relative error . Lastly the neural network is applied to the test data to determine the answer to the research question for which it was developed. The test data also measures the final performance of the NN.

Various algorithms are available to assist during the development of the NN. The Kennard-and-stone algorithm can be applied to assist in selecting proper training and validation datasets [13]. the Back-propagation through time (BPTT) enables the RNN to increase its convergence speed. The Nguyen– Widrow algorithm helps decrease training time by providing a method for determining the initial weights of the NN [1]. Bayesian regularization [11] can be used during the training stage to skip the validation stage[15].

3.1.2 Genetic algorithm

The genetic algorithm (GA) is an evolutionary algorithm based on Darwin's theory of natural selection and evolution [13]. At the start an initial population consisting of chromosomes (feasible solutions) is randomly generated. Each individual or solution is evaluated according to the fitness function. The fitness or objective function is a user specified criteria which determines the output variable value of a solution given its input variable characteristics (its genes) [16]. Three primary genetic operations occur to create the next generation or population in order to explore the solution space: reproduction, crossover and mutation.

During reproduction parent chromosomes are randomly selected or selected according to their fitness value, to create offspring and they are duplicated [13]. Crossover is the process where genetic material is exchanged between the two duplicated parents by randomly selecting a crossover point and swapping their 'genes' to create two offspring which are different from the parents. Single-point or multi-point crossover can occur. During mutation a random chromosome and random mutation point on the chromosome is selected. The value of the selected ‘gene’ is then altered or in the case of binary ‘genes’ a 1 becomes a 0 and vice versa. Figure 2 shows the genetic algorithm and the processes of crossover and mutation. The elitist members of the current population, the non-dominated chromosomes, are selected and added, together with the offspring (some are mutated), to create the next population. GA parameters include mutation probabilities, mutation rate, crossover point probabilities, crossover rate, reproduction probabilities, reproduction rate, elitism number (number of good solutions in current population which are transferred to next population), population size number of generations, etc.

Variations on the GA are available, including genetic programming (GP), gene expression programming (GEP) [17], multi-gene GP (MGGP) [18], non-dominated sorting genetic algorithm (NSGA) and particle swarm optimization (PSO) [19]. The key difference between GA and PG are the following: GA evolves fixed length binary or real valued strings while GP evolves tree structures called models which can vary in length throughout the evolution [2]. GA works with chromosomes while GP works with computer programs (mathematical formulas, computer programs, logical expressions, etc.). GP also incorporates genetic operators like gene/tree duplication and deletion [13]. GEP is developed from GP and the only modification is that models are represented in Expression Trees (linear structure) which simplifies the diversity of the tree population [17]. MGGP is a variant of GP where each evolved model is a combination of trees/genes whereas in GP, each evolved model is a single tree/gene.

The NSGA is a variation of the GA, developed for multi-objective optimization problems, where groups or fronts of non-dominated optimal solutions are determined by using the rank of the group, the crowding distance and the fitness value. All the solutions are evaluated, and the first front is the group of non-dominated optimal solutions (solutions which are equally good compared to other solutions from the same front). This process is called the first sorting and the non-dominated solutions are given a rank of 1. During the second sorting the remaining solutions are evaluated with the same process and this process repeats until all the solutions have been given a rank [20].

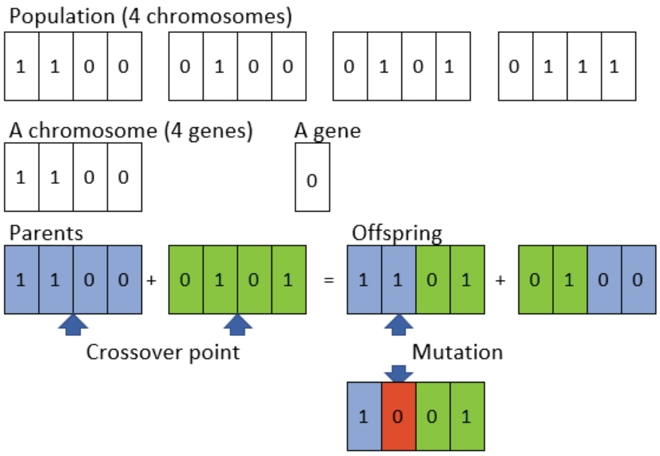

Figure 2: The genetic algorithm.

The PSO was developed to solve continuous optimization problems. The algorithm is based on the foraging behavior of a swarm of birds or fish. It enables the competition model using GA and ensures cooperative behavior among individuals (birds or fish) [19]. The population is called the swarm and it is composed of volume-less particles (feasible solutions) with stochastic velocities (a vector of independent variables). For each generation the global best solution and the best solution so far of every particle is recorded to determine the new velocities of each particle in the next generation. The new velocities also depend on the previous velocity of the particle, the cognitive learning parameter (the confidence the particle has in itself), the social learning parameter (the confidence the particle has in the swarm) and the inertia weight (controls the search skills of the swarm). The velocity updating formula is available in [21] and the algorithm steps in [22]. The algorithm finds the optimal solution by letting the particles ‘fly’ through the solution space. PSO parameters include swarm size, generation limit, maximum global velocity, maximum particle velocities, inertia weight, social and cognitive parameters

3.1.3 Other machine learning algorithms

Other evolutionary and swarm intelligence-based algorithms include bidirectional evolutionary structural optimization (BESO) [23], bacteria foraging optimization algorithm (BFOA) [24] [25], mutable smart bee algorithm (MSBA) [26], quantum-behaved particle swarm optimization (QPSO) [27] and differential evolution (DE) [14].
Additional classification approaches include decision tree (DT), k-nearest neighbor (KNN), support vector machine (SVM) [28], Linear Discriminant Analysis (LDA), and Quadratic Discriminant Analysis (QDA) [29].
Further learning methods include grey relational analysis [5], random order heuristic [30], cross-coupled path pre-compensation (CCPP) algorithm [31], Graph theory [32], gradient descend algorithm [33], geometric algorithm [34], simulated annealing (SA) [30], adaptations of the solid isotropic material with penalization

algorithm (SIMP) [35], fuzzy logic [36] [37], finite element analysis (FEA) or finite element method (FEM) [38], regression modelling [39] and response surface methodology (RSM) [40].
Hybrid models include a combination of fuzzy inference system and a neural network, called adaptive neuro fuzzy inference system (ANFIS) [41]. An ANN (to model the problem) and GA (to optimize the problem) have been combined in [42].

3.2 Machine learning applications in additive manufacturing

Traditionally process parameters are determined by the operator's experience [1], the conservative technological data provided by the additive manufacturing equipment manufacturers [9] and trial-and-error operations. This leads to inconsistent machining performance since operator's experience is limited and subjective while the manufacturer data is based on safety-conscious principles and it only includes applications on certain machining materials. New materials are constantly developed, for example titanium alloys, aluminum alloys, advanced plastics, etc. Trail-and-error operations employ post-process techniques to inspect the quality of the finished product [1]. This methodology includes a range of disadvantages: it is costly, time-consuming and it leads to numerous defective and useless products which are only discovered once the process has been completed.

Machine learning addresses these resource efficiency challenges by determining the optimal process parameters given an objective(s) through simulations without repeatedly producing physical products. Machine learning also increases sustainability since it leads to the permanent availability of uniform, objective AM process knowledge (manufacturers do not have to hire costly consultants repeatedly), it enables manufacturers to optimally benefit from their machining equipment without the acquisition of new costly, carbon-footprint related equipment and it reduces the usage of valuable resources including time, money, energy and natural resources. Machine learning also enables product safety, since it can be used proactively to allow one to view the AM parameters before application. Thus harmful or inadequate parameters can be identified before the process started.

Machine learning algorithms have been applied to a variety of additive manufacturing process types including 3D printing (3DP), directed energy deposition (DED) [43], electron beam melting/manufacturing (EBM), fused deposition modelling (FDM), laser engineered net shaping (LENS), laminated object manufacturing (LOM), stereolithography (SLA), selective laser cladding (SLC), selective laser melting (SLM), selective laser sintering (SLS) and wire + arc additive layer manufacture (WAALM). Table A in Appendix A provides a detailed summary of the different additive manufacturing processes and the different machine learning algorithms applied in these processes, according to the review. Fig. 3. illustrates the additive manufacturing processes supported by machine learning applications. The percentages indicate the relative ratios. It is evident that FDM is the field in which the most applications have been applied, followed by SLC, SLS and AM in general applications.

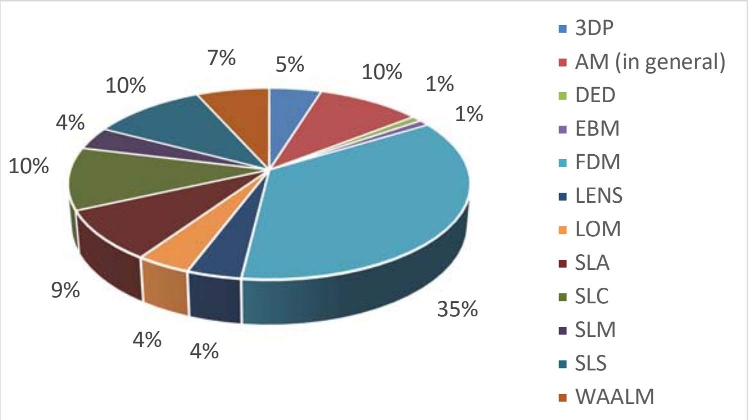

Fig 3. Additive manufacturing processes supported by machine learning applications.

Fig. 4. illustrates the different types of machine learning algorithms which have been applied in AM processes. ANNs are the most common application, followed by GA, regression modelling and RSM.

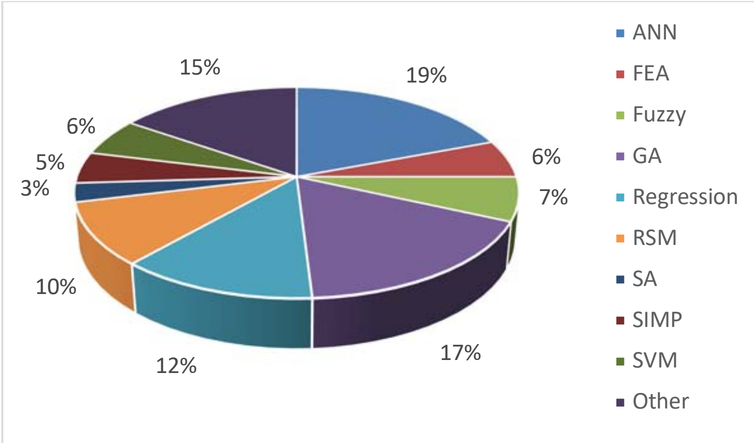

Fig 4. The different types of machine learning applications applied in AM processes.

3.3 The process of applying machine learning techniques

From the systematic review, the author learned of the process of applying machine learning techniques in additive manufacturing processes, as illustrated in Fig. 5. The pre-settings on the additive manufacturing machine include the independent variables which the machine operator has control over. The sensors measure the dependent variables, which is a result of the additive manufacturing process and it takes the measurements continuously throughout the process. Pre-processing of the output data of the process include: labelling, dimension reduction techniques and frequency and time-frequency domain signal processing techniques. Labelling is the process of connecting the output value to the corresponding input variables. Labelling would be used in the case of preparing the training data so that the model can learn to accurately predict the objective value, by measuring its error of prediction and adjusting itself to minimize the error. Dimension reduction techniques are used to reduce the dimension of the input data of the machine learning technique by transforming the original data to a smaller dimension while the variance of the original data is preserved. This supports the model by ensuring that it is less computational intensive to develop. Next, the machine learning techniques are applied to the processed data and the resulting information undergoes post-processing. Post-processing of the information includes the validation of the model, testing of the model and comparing the performance of the model to other machine learning models.

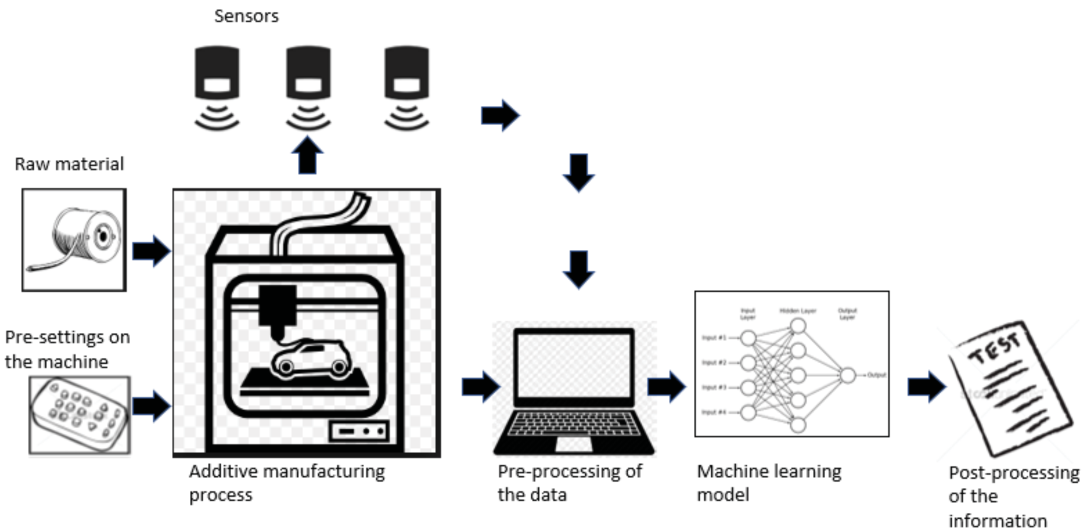

Figure 5. The process of developing machine learning models in additive manufacturing.

4. CONCLUSION

In the manufacturing industry machine learning can lead to cost savings, time savings, increased quality and waste reduction. At the same time, it enables systems to be designed for managing human behavior. From the systematic review, the author learned of the different machine learning techniques which have been applied to additive manufacturing processes, the machine learning trends in these manufacturing processes and the process of applying machine learning techniques in additive manufacturing processes.

Appendix A. Different cutting processes versus different machine learning algorithms.

The following table shows the different additive manufacturing processes and the machine learning techniques which have been applied in them, per reviewed study. An ‘H’ superscript indicates that the study used a hybrid or combination of machine learning algorithms, while an ‘&’ superscript indicates that various algorithms were compared in the study.

Table A: Different additive manufacturing processes versus different machine learning algorithms.

Machine learning method	*ANN*	*FEA*	*Fuzzy*	*GA*	*Regression*	*RSM*	*SA*	*SIMP*	*SVM*	*Other*	*Total*
3DP				[44], [16]				[35]H,		[33], [35]H,	5
AM (in general)		[19]H,	[37], [36]	[19]H,	[5]H,		[30]H,			[23], [30]H, [5]H, [32]	10
DED		[43]									1
EBM		[8]									1
FDM	[1], [14]H, [11], [2]&, [9]&, [13]&, [27]&, [25]H, [45]H,	[38]H,	[10]H, [4], [46]&,	[10]H, [14]H, [2]&, [9]&, [13]&, [27]&, [46]&,	[2]&, [47] [48]&, [49] , [45]H,	[10]H, [24]H, [50],		[3], [38]H,	[9]&, [51], [46]&,	[24]H, [25]H, [48]&, [34]	37
LENS	[28]&,								[28]&, [29]&,	[29]&,	4
LOM				[52],	[53],	[54],				[31]	4
SLA	[42]H, [55]H,	[38]H,		[42]H, [55]H,		[56],	[55]H,	[38]H,		[34]	9
SLC	[12], [41]H, [26]H,		[41]H, [26]H,	[26]H, [57],		[40], [58]H,				[58]H, [26]H,	11
SLM	[59]&,			[59]&,		[60],	[61],				4
SLS	[18]H, [62]&,	[38]H,		[18]&,	[63], [64],	[62]&, [65],		[38]H,	[18]H,	[18]H,	11
WAALM	[66], [67]&,			[17]	[39], [67]&, [68], [69],						7
Total	20	6	7	18	13	10	3	5	6	16	

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