Thermal Predictions in Additive Manufacturing using Machine Learning

A report for the First phase submitted in partial fulfilment of the requirements for completion of the Dual Degree project

Submitted by

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Abstract

Additive manufacturing is the process of creating an object by building it up layer by layer. It is the opposite of subtractive manufacturing, in which an object is created by cutting away a solid block of material until the final product is complete. Technically, additive manufacturing can refer to any process that creates a product by building something, such as moulding, but it typically refers to 3-D printing.

Finite Element Analysis (FEA) is a computer-aided method for predicting how a product will respond to real-world forces, vibration, heat, fluid flow, and other physical effects. Finite element analysis reveals whether a product will break, wear out, or perform as designed, but is often the most expensive and time-consuming aspect of additive manufacturing.

This study aims to reduce the need for time-consuming and expensive finite element simulations. We believe these insights are an essential step towards real-time optimization in AM.

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Nomenclature

AM	Additive Manufacturing
ANN	Artificial Neural Network
3D	3-Dimensional
FDM	Fused Deposition Modeling
FEA	Finite Element Analysis
FFNN	Feed-Forward Neural Networks
ERT	Extra Tree
LBAM	Laser-based Additive Manufacturing
a	pass width
a_f	front semi-axes of double-ellipsoid heat source model
a_r	rear semi-axes of double-ellipsoid heat source model
f_f	fraction of deposited heat in front quadrant of double-ellipsoid heat source model
f_r	fraction of deposited heat in rear quadrant of doubleellipsoid heat source model
h_b	height of printing base
Q	power input
T_{am}	ambient temperature
v	print speed

Chapter 1

Introduction

1.1 Background of the Project

Additive Manufacturing (AM) is an emerging technology for the industrial manufacture of 3D parts. To date, AM is used in many industries, especially in cases where manufacturing complicated designs, small series or one-off manufacturing is important. AM parts are built from a computer model by iteratively adding thin layers of material. The process of constructing AM parts involves melting material through a focused energy source, followed by rapid consolidation.

The steep thermal gradients and uneven expansion and contraction of the material during thermal cycling can significantly affect the performance of the printed part by reducing fatigue life and corrosion resistance, and increasing crack propagation, porosity, and geometric distortions. Because physical experiments are expensive, computer simulations are essential in the design and optimization process to build robust and reliable parts.

However, due to complex boundary conditions and incremental element activation associated with gradual material deposition, modeling the AM process has high computational costs in terms of processing time, memory, and computational requirements (*Jiang et al., 2020*). Recently, researchers have become interested in integrating finite element simulations (FE) and machine learning (ML) for real-time prediction of the AM process, with ML models predicting the behavior of expensive numerical methods.

Because of the high redundancy, repeatability, and periodicity of the AM process, the process lends itself well to ML. Machine learning implemented in AM is currently being developed as a lower-cost alternative to physics-based numerical models, where ML can speed up design and development in AM by enabling rapid screening of parts.

1.2 Research Outline

The report structure is as follows:

Chapter 1: This chapter includes the introduction to the topic and includes the project's background and the objectives for the study that will be carried out in the future

Chapter 2: This chapter gives a brief literature review of the State-of-the-art of machine learning models for thermal predictions in additive manufacturing, their achievements, performance, utility and limitations

Chapter 3: This chapter defines the project roadmap and its key highlights

Chapter 4: This chapter illustrates the work done & milestones achieved so far on the initial steps of the proposed blueprint of the overall project

Chapter 5: This chapter focuses on the way ahead in the project timeline

Chapter 6: This chapter shows the reference materials used during the study

Chapter 2

Literature Review

2.1 Past Studies & Publications

As part of the project research, a collection of research papers published relevant to the project was examined and based on these observations, insights and conclusions were extracted.

Several studies have proposed efficient, high-performance ML models, and the basic framework for predicting thermal properties in AM have already been established in previous works. The following briefly illustrates the same:

Mozaffar et al. (2018)

- Proposed a data-driven approach to predict thermal behavior in a Directed Energy Deposition (DED) process using time series in recurrent neural networks (RNN).
- The model can perform reasonably well on material points with similar geometric features as the training database
- But, it has limited transferability to complex geometries where the geometric feature and boundary state are distinguishable from those of the trained material points

Stathatos and Vosniakos (2019)

- Proposed a custom scan path decomposition method and used artificial neural networks (ANN) to predict the temperature evolution for arbitrarily long paths in laser-based additive manufacturing (LBAM)
- However, the model has only been demonstrated by predicting the thermal field of a single-layer AM model

Paul et al. (2019)

- Used extremely randomized trees (ERT) and an ensemble of bagged decision trees as a regression algorithm for real-time prediction of thermal profiles in the DED process.
- In the model, the temperatures of previous voxels and laser information are used as inputs to predict the temperatures of subsequent voxels.
- However, since the ML model used a feature set based on neighboring voxels with a uniform mesh of rectangular elements, the model would have to be modified to generalize to irregular geometries and meshes

Ren et al. (2020)

- Introduced a physics-based ML model that used deep neural networks (DNNs) combining RNNs to build the relationship between scan patterns and the corresponding thermal field.
- This model achieved more than 95% prediction accuracy for any scan pattern but its geometries were demonstrated limitedly on a single slice only

Zhou et al. (2021)

- Put forward a 3D corrected matrix to represent the cube-mesh-based laser deposition status and entered it as inputs for an RNN & DNN model
- The model exhibited good performance on diverse geometries and deposition patterns
- But, since the curved edges are incapable of meshing into perfect cubes, the units of the 3D matrix cannot accurately represent the state of deposition of the mesh close to the edge

All of the above models either depend on a large amount of data to learn the interrelationship between high-dimensional inputs and outputs or are based on certain cases with specific low-dimensional inputs and outputs

In order to tackle this issue, some physics-based ML models have been generated by using input features that can denote the physical processes undergoing in various AM models or manufacturing processes.

2.2 Previously established Physics-based ML Models

Roy and Wodo (2020)

- Proposed a group of distance-based features by consolidating the characteristics of the thermal processes in fused deposition modelling (FDM) and created a neural network model that needed smaller datasets in comparison to the ML models proposed earlier
- The ML model had a shorter training duration and reached a competitive accuracy, designating the ML model as capable enough for in situ estimations
- But, as a result of non-generic features based on the distance from cooling surfaces, the ML model was only appropriate for simple, rectangular geometries

Roy and Wodo (2021)

- Attempted to deal with the challenges in *Roy and Wodo (2020)* and optimized the physics-based feature set and output
- The proposed ML model is applicable to various structures, but a few of the proposed features depend on seeding in the FEM mesh, which means that the features have limited applicability to complex geometries where the element size is usually not homogeneous

Fetni et al. (2021) & *Pham et al. (2021)*

- Introduced a set of input characteristics identifying the positions of calculated point, laser heat source and deposition time and trained an ANN model to replicate the temperature fields in DED
- Input energy and the number of current printing layers were added to *Fetni et al.'s* feature set and used feed-forward neural networks (FFNN) to predict the thermal profile
- But the geometric feature and the boundary states are not taken into account in these models. Therefore, they are only suitable for samples with simple geometric shapes

Even though some ML models performed well in the thermal predictions of specific cases, the applicability of these ML models is still restricted by non-generic features that are incapable of handling varying simulation properties

As a concluding remark, due to several simplifications, the existing ML models put forward by the scientific community deviate from the realistic results when product properties for example geometry and pattern of deposition become relatively complex.

Paper	**Process**	**Model**	**Predicted Value**
Mozaffar et al. (2018)	DED	RNN	Stepwise nodal T
Paul et al. (2019)	DED	ERT	Ts of subsequent voxels
Stathatos & Vosniakos (2019)	LBAM	ANN	Sequence of local Ts
Ren et al. (2020)	LBAM	RNN	Laser deposition matrix
Roy and Wodo (2020)	FDM	ANN	T profile coefficients
Roy and Wodo (2021)	FDM	ANN	Consolidation degree
Pharm et al. (2021)	DED	FFNN	Stepwise nodal T
Fetni et al. (2021)	DED	ANN	Stepwise nodal T
Zhou et al. (2021)	DED	RNN	T state data

Table 2.1

Summary of the existing ML models for thermal prediction in AM, where T is temperature

Chapter 3

Project Roadmap & Key Highlights

- The work aims to develop a generic feature set that entails the thermal processes without depending on simplifications of the parts. The resultant feature set shall be physics-based which can generalize across various geometries, deposition patterns, and power intensities and are drawn out based on the fundamental thermal processes in AM.
- The features will be trained and tested on datasets that have been generated through numerical simulations of the thermal processes in additive manufacturing.
- These datasets will be generated to demonstrate different process characteristics such as deposition patterns, heat input, and geometry.
- The approach will present multiple ML models trained on different datasets and tested to ensure the generalizability of the ML models when trained on different part properties.
- The ML models should display promising results in both same-simulation and simulation-to-simulation predictions.
    - Same-simulation signifies the case where the ML model is trained and tested on data from the same simulation.
    - Whereas, simulation-to-simulation predictions are trained and tested on data from distinct sets of simulations.
- Noticeably, the ability to carry out simulation-to-simulation predictions will decrease the time and computational cost as compared to conventional numerical methods.
- Therefore, it is expected that this work can drive the AM community closer to bringing about the development of an extensive data-driven real-time control system for thermal predictions of AM processes.

Chapter 4

Current Work

4.1 Data Generation through FE Simulations

To generate the data sets for training and testing in the ML model, finite element simulations were performed using the ABAQUS software along with the additive manufacturing module plugin. For all simulations, the arc wire additive manufacturing process is studied, and the pass width and layer thickness are 10 mm and 2.23 mm, respectively. The material of the substrate and the deposited parts is Aluminium alloy 2319 (AA2319). The density is 2823 kg/m^3. The liquidus temperature and the solidus temperature are 643°C and 543°C, respectively.

A double ellipsoidal heat source model is used in the FE models, and the values of the associated parameters are presented in Appendix A. The element type used in the FE model is an 8-node linear heat transfer brick. The thermal analysis considers thermal conductivity, thermal convection, and radiation. Thermal property parameters are given in Annex A. Both the initial temperature of the substrate and the ambient temperature are 20°C. The deposition speed is 10 mm/s. The elements and material properties are activated at the appropriate time based on the deposition sequence under different patterns. After deposition, the model cools down naturally to room temperature.

The data sets include data samples from multiple finite element simulations with different deposition patterns, dimensions, geometries, power input intensities and other process parameters. This was done to examine the transferability of the extracted feature space and the ML model to multiple cases. An example of the generated FE models is shown in Fig. 1, and an overview of the different geometries and deposition patterns of the simulations is shown in Fig. 2. The variables of the simulations can be seen in Table 2 and the rest of the simulation properties, which are constant for all simulations, can be seen in Appendix A.

Each data sample in the data sets represents the transient properties of a node at a specific point in time. All simulations were performed with the inactive activation strategy, which means that the elements representing the deposited material are not considered until the material is deposited and the element is activated. This implies that the dataset contains only data samples from checked items and that the items in the base are not included in the dataset. All simulations were sampled at the simulation increments, meaning that the samples were not evenly spaced in time.

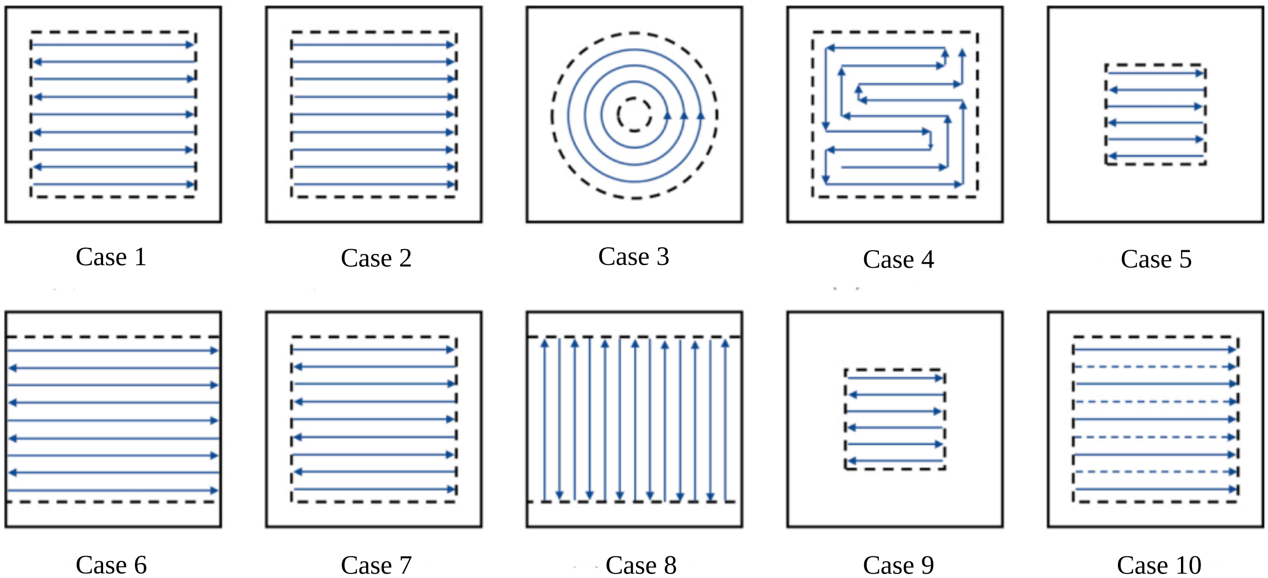
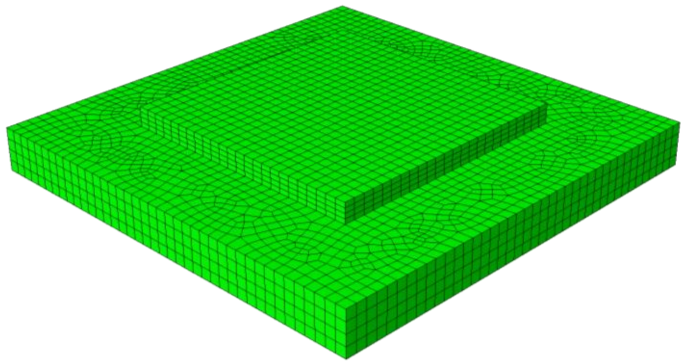


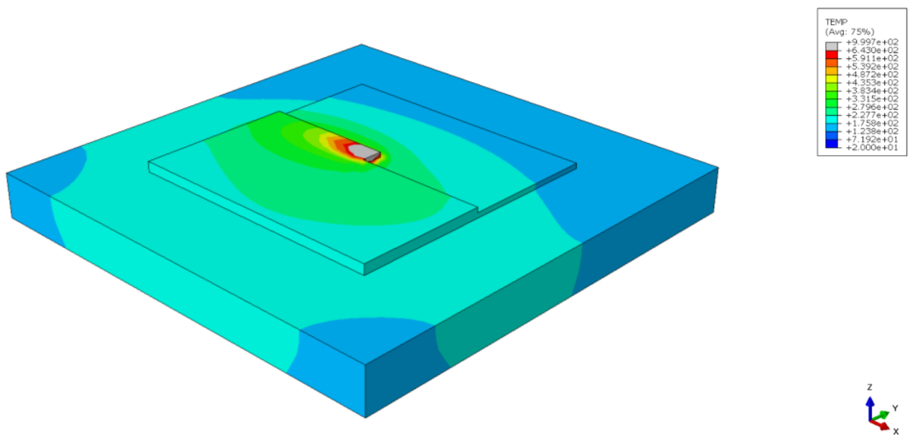
Fig. 4.1
Images illustrating geometry and deposition patter of all simulation experiments in the complete dataset. Here, black lines => base, black dashed lines=> deposition geometry & blue arrows => laser direction

Case	Q (kW)	Dimensions (m^3)	Elements	Pattern
1	5	0.12 * 0.12 * 0.0092	9600	ZigZag
2	5	0.12 * 0.12 * 0.0092	9600	Raster
3	5	π * 0.12^2 * 0.0092	9672	Out-in spiral
4	5	0.12 * 0.12 * 0.0092	9600	S
5	5	0.06 * 0.06 * 0.0092	8148	ZigZag
6	5	0.12 * 0.16 * 0.0092	9812	ZigZag
7	5-4	0.12 * 0.12 * 0.0092	9600	ZigZag
8	5	0.12 * 0.16 * 0.0092	9812	ZigZag
9	5-2	0.06 * 0.06 * 0.0092	9012	ZigZag
10	5	0.12 * 0.12 * 0.0092	9600	Alternate-line

Table 4.1
Simulation Summary

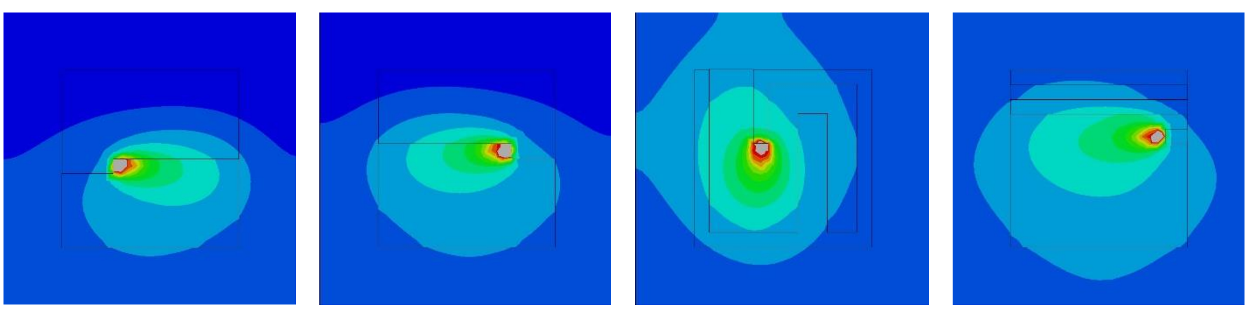


(a) Mesh



(b) Thermal Field (temperature) contour plot (for case 1)

Fig. 4.2
FE models generated in the work



(a) ZigZag (b) Raster (c) S (d) Alternate-line

Fig. 4.3
Thermal fields contour plots of selected FE models with varying deposition patterns for 1st layer (deposition in progress)

Chapter 5

Future Work

5.1 Future Work Feature Engineering for Data Refining

In this part of the project work, feature engineering, that includes techniques to clean and organize data making them suitable enough for machine leaning pipelines, will be carried out. Domain knowledge would be utilized to extract features from the raw data obtained through the previous step of data generation. This would enable better representation of the problem being studied which is of considerable significance as good feature engineering will pave way for enhanced ML model performance.

From the raw data generated by FEA, a generic feature space would be extracted based on the underlying physics of the thermal processes that occur during AM. The feature set would be expected to not rely on specific properties and therefore, would not mandate tweaks to handle simulations with different geometries, meshes, deposition patterns or boundary conditions.

The feature space will be well-defined and reasoned for being included in this section.

5.2 Machine Learning Modelling

The developed features based on the thermal behaviour in additive manufacturing processes would be expected to be independent of the simulation. Thus, it would make them possible to be applied on thermal predictions of computational models with a different thermal characteristics. The features will have to be tested and validated by carrying out ML experiments.

A brief study has been done so far in the interest of this project to lay the foundational understanding of suitable ML modeling to achieve the desired outputs and the following worth mentioning notes were made:

- It has been established in previous works (Paul et al. 2019) that among various regression methods that were tested, Extremely Randomized Tree, popularly known as Extra Trees (ERT) achieved the best performance
- ERT have an edge over other methods in terms of simplicity, optimizability, understandability and robustness to heterogenous and noisy data
- ERT are also one of the most computationally efficient while also attaining competitive accuracy values
- To achieve a competitive level of accuracy in predictions, one usually has to aggravate methods with various trees to compete with other advanced ML methods such as neural networks in terms of performance

Therefore, the background research for ML modeling suggests to firstly consider ERT and proceed with studying it in-depth, consequently attempting it to deploy it for ML modeling.

Appendix A

Table A.1: Details of simulated AM models

Material Properties	Material	AA2319
Boundary conditions	Thermal	Constant base temp. (T_{am})
Geometrical properties	Base height (h_b)	0.02 m
Process parameters	Layer thickness	0.0023 m
	Pass width (a)	0.01 m
	T_{am}	20 °C
	Print speed (v)	0.015 m/s
Mesh details	Element size	0.005 m
	Element type	DC3D8
	Integration	Full
Deposition details	Activation offset	0.005 m
	Activation set size	(0.005 x 0.01 x 0.0023) m^3
	Heat source model	Double ellipsoid
	a_f	0.002 m
	a_r	0.004 m
	f_f	0.6
	f_r	1.4
	Layer break	10 s

Fig A.1: Temperature dependent properties of AA2319

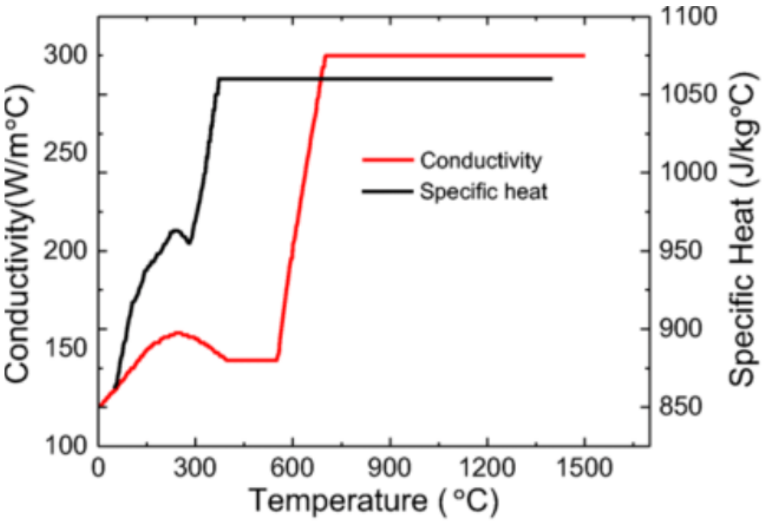


Table A.3: Temperature independent properties of AA2319

Mass density	2823 kg/m^3
Liquidus temperature	643 °C
Solidus temperature	543 °C

Chapter 6

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