Machine learning attitude towards temperature report forecast in additive manufacturing procedures

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ABSTRACT
Additive Manufacturing (AM) is a manufacturing paradigm that builds three-dimensional objects from a computer- aided design model by successively adding material layer by layer. AM has become very popular in the past decade due to its utility for fast prototyping such as 3D printing as well as manufacturing functional parts with complex geometries using processes such as laser metal deposition that would be difficult to create using traditional machining. As the process for creating an intricate part for an expensive metal such as Titanium is prohibitive with respect to cost, computational models are used to simulate the behavior of AM processes before the experimental run. However, as the simulations are computationally costly and time- consuming for predicting multiscale multi-physics phenomena in AM, physics-informed data-driven machine-learning systems for predicting the behavior of AM processes are immensely beneficial. Such models accelerate not only multiscale simulation tools but also empower real-time control systems using in-situ data. In this paper, we design and develop essential components of a scientific framework for developing a data-driven model-based real-time control system. Finite element methods are employed for solving time-dependent heat equations and developing the database. The proposed framework uses extremely randomized trees - an ensemble of bagged decision trees as the regression algorithm iteratively using temperatures of prior voxels and laser information as inputs to predict temperatures of subsequent voxels. The models achieve mean absolute percentage errors below 1% for predicting temperature profiles for AM processes.

KEYWORDS: Machine Learning, Additive Manufacturing, Ensemble Learning, Modelling

1.0 INTRODUCTION

Additive Manufacturing (AM) is a modern manufacturing approach in which digital 3D design data is used to build parts by sequentially depositing layers of materials. AM techniques are becoming very popular compared to traditional approaches because of their success in building complicated designs, fast prototyping, and low-volume or one-of-a-kind productions across many industries [1-7]. Direct Metal Deposition (DMD) is an AM technology where various materials such as steel or Titanium are used to develop the finished product. Computational simulations are an essential part of the AM design and optimization as they eliminate the trial and error on expensive manufacturing processes. Finite element-based multi-physics simulation models (FEM) are designed to replicate the AM process before generating the required part using AM. However, FEM-based simulations are computation- ally costly and time-consuming [8-17]. This leads to the motivation to develop a predictive tool based on machine learning (ML) that can instantaneously yield the simulation result instead of performing expensive physics-based simulations. A real-time AM control system can be useful in manufacturing because it can control machines considering the changes in the environment and the machine itself [18-25]. This can be more important in AM since most of the vital parameters in the quality of final product change considerably during the build process. The temperature field created while building a part using AM is one of the critical components in determining microstructure, porosity, and grain size. This system requires a fast data-driven predictive model that can relate machine parameters and replicate desired property behavior accurately using ML techniques, without the need for computationally expensive calculations. There has been an upsurge of interest in the manufacturing community to connect and share data be- tween geographically distributed facilities [26-33]. We believe a significant amount of experimental data will be available in the near future for manufacturing processes, especially AM. This urges the scientific community to develop suitable data- driven tools and techniques. In this work, we use Generalized Analysis for Multiscale Multi-Physics Application (GAMMA), a FEM based method for developing the database to train our model-based control system [34-42]. GAMMA is used to solve the time-dependent heat equation and simulate the manufacturing DMD process at the part scale. As the AM process is a spatiotemporal phenomenon (since there is cooling and reheating depending on whether and when a neighboring element is created), any approach for predicting the temperature profile must include the information about neighboring voxels as well as temporal information. In our proposed approach, we harness this characteristic of the AM process during feature reconstruction for our learning system [43-54].

2.0 LITERATURE REVIEW

The heat flow during DED is a quasi-stationary process, with respect to moving arc heat source. To be specific, the temperature distribution in the melt pool surface does not change with time except for initial and final transients. Thus, thermal sensing techniques are an effective way of monitoring DED. Thermal methods are fast when compared to other non-destructive testing methods such as ultrasonic, for quality monitoring of process [1-4]. It is a very feasible process and allows rapid results during manufacturing of parts. Every object emits electromagnetic radiation from its surface proportional to its temperature. This intrinsic radiation associated with temperature is called infrared radiation and can be used for temperature measurement. Khanzadeh et al. developed a thermal sensing system with a pyrometer and IR camera to analyze the temperature changes in laser-based AM process [5-9]. The melt pool images were analyzed using self-organizing maps (SOM). The pro- posed methodology was able to detect the porosity locations with an accuracy of 85%. Sreedhar et al. developed an online monitoring system for gas tungsten arc welding (GTAW) using thermal images. The authors noticed a distinctive pattern at the defective locations over non-defective areas. Mireles et al. proposed in-situ monitoring technique for defect detection [10-14]. The authors mapped the results obtained from computed tomography (CT) and layer-wise thermography to find defects. Krauss et al. developed a model to detect flaws in selective laser melting (SLM) process using thermography measurements of molten pool [15-21]. Analytical models of temperature distributions of wire-based DED have been extensively studied in literature. Rosenthal and Rykalin developed analytical models to calculate weld dimensions from temperature distributions of moving point heat source. Several analytical models have been developed for additive manufacturing processes. Pinkerton and Li derived a model that is applicable for low travel speeds from Rosenthal equations [22-28]. Beuth and Klingbeil developed analytical model to predict melt pool length. However, the performance of analytical models for in-situ monitoring of additive manufacturing processes is questionable. Also, physics-based analytical models cannot address the uncertainties and variances that occur during a process. Numerical models of additive manufacturing processes have been shown to be efficient in predicting thermal profile given all the boundary conditions. Hejripour et al. developed a fluid flow and heat transfer model for WAAM process [29-34]. The author predicted the shape of deposited material for single layer using an arbitrary LagrangianEulerian method. Kou proposed a 3D model of WAAM process to predict material dimensions and temperature distributions from machine operating parameters. The model was developed by taking into account electromagnetism, fluid flow and heat transfer. Zhang et al. derived a relationship between thermal profile and microstructures evolution in melt pool by using finite element method. Numerical models have some important limitations that include high computational costs, oversimplified assumptions and various meshing schemes. Data-driven models of melt pool temperature during DED processes have recently gained a considerable amount of interest among the researchers. Khanzadeh et al. detected porosity in additively manufactured samples from melt pool temperature profile using supervised machine learning techniques [35-42]. The extracted features of melt pool images were fed to k-nearest neighbor (kNN) method and the predicted results were in good coherence with experimental results. Mozaffar et al. estimated high-dimensional thermal profile in DED process using the large amount of data obtained from the fine element code. A gated recurrent unit (GRU) model was used to predict the temperature profile and the results of model shown high accuracy. However, general applicability of these models are questionable due to the stand-alone models used [43-51]. For example, in CMT technology, the process behavior leads to a seasonal trend and that need to be addressed during forecasting. The stand-alone models may fail to understand the process profoundly. In recent years, many researchers have combined CNN and LSTM model to exploit the benefit of spatial and sequential features in variety of applications. Huang et al. proposed a particulate matter (PM2.5) concentration forecasting system by combining CNN and LSTM networks. Further, the authors evaluated model using MAE and RMSE and concluded that the performance of model is better than the traditional machine learning models [52-57]. A similar work was reported for forecasting PM2.5 using CNN-LSTM network. Kim et al. proposed a hybrid CNN-LSTM model to predict the residential electrical energy consumption and analyzed the various variables that affect the prediction of energy consumption. Rehman et al. improved the accuracy of movie reviews sentiment analysis [58-63]. A considerable amount of research has been conducted in the field of natural language processing using CNN-LSTM networks. In the field of medical image processing, Petmezas et al. developed an automatic atrial fibrillation detection system from electrocardiogram (ECG) signals using CNN-LSTM network with a high sensitivity and specificity. Vidal et al. used CNN-LSTM network to predict the future volatility of gold prices and the performance is compared with the other classic models. The CNN-LSTM network proved to be a potential technique in forecasting time series and opening up new possibilities in various areas of applications. system include the distance of a given voxel from the current laser beam in the x, y and z axes, laser intensity, time at which the point is created, the time elapsed, and tool speed [64-70]. One of the advantages of a real-time system is instead of training a prior model ahead of time, one can be developed in-situ. This is crucial for the versatility of ML-driven control system, especially as factors such as laser path, laser speed, and laser temperature can largely influence the temperature profile in AM processes which in turn can predict presence of residual stress. Residual stress caused in AM is the critical issue for fabricated metal parts since steep residual stress gradients generate distortion which dramatically deteriorate the functionality of the parts. The proposed approach uses extremely randomized trees (ERTs), a tree-based ensemble algorithm to iteratively train a model-based control system. A model is developed on the features of first m voxels to predict the temperature of next n voxels at the first stage, and then iteratively a new model is developed at every subsequent stage using the ground-truth temperature of m voxels as well as the predicted temperatureof the n voxels [71-79].

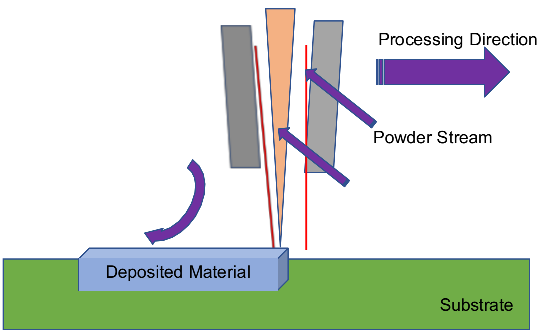

Fig b: DMD overall setup

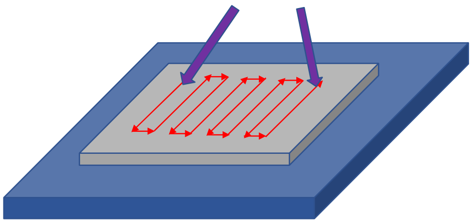

Fig b: DMD Laser Path on Substrate

Fig. 1. Additive Manufacturing using Direct Metal Deposition (DMD) process. The laser source provides the heat while the powder stream provides the metal for the deposition. The metal powder gets melted by the heat from the laser beam and deposited on the substrate. The laser scans overthe substrate in a zigzag motion.

The result of this work is a real-time iterative supervised predictive model that achieves % mean absolute error (% MAE) below 1% for predicting temperature profiles for AM processes. The iterative model outperforms a tradi- tional model that does not use predicted intermediate voxel temperatures. The code is made available for the research community [3-9]. The rest of the paper is organized as follows. Section II provides a brief background of AM and DMD, and the FEM code used for developing the database and some related works for application of machine learning in materials informatics, and specifically AM. In Section III, we explain the generation and transformation of the dataset and describe the input features and voxel categories. We describe the motivation and methodology and development of the dataset in Section IV. We discuss the experimental settings and results in Section V, and finally in Section VI, we summarize our conclusions with some future directions [11-18]. The initial development process for creating a three-dimensional object using computer-aided design (CAD) for a layer by layer deposition was realized due to a desire for rapid prototyping, It reduced the time-cycle of realizing an initial prototype after the conception of de- sign by engineers. Among the major advances that this process presented to product development are the time and cost reduction, and the shortening of the product development cycle. Further, it led to the possibility of creating shapes that were difficult to be machined using traditional manufacturing processes. AM can appreciably reduce material waste, decrease the amount of inventory, and reduce the number of distinct parts needed for an assembly. Further, AM can reduce the number of steps in a production process, both in the case of tool making as well as direct manufacturing, reducing the need for manual assembly. Besides, AM processes can significantly reduce the total amount of tooling required and its impact on the cost. AM parts can be manufactured in an almost final state, thus reducing the amount of connecting parts required to put them together and decreasing part count [19-28].

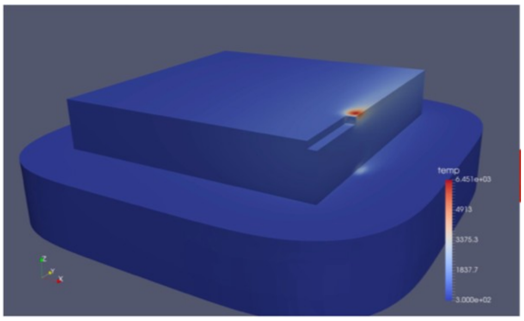

Fig. 2. The simulated metal surface built using DMD is depicted in the figures. The first figure demonstrates the metal created using DMD on the substrate with the temperature scale. The color of the metal surface indicates the spatio-temporal characteristic of the DMD process.

DMD is an additive manufacturing technology using a laser to melt metallic powder. DMD processes can produce fully dense, functional metal parts directly from CAD data by depositing metal powders using laser melting and a patented closed-loop control system to maintain dimensional accuracy and material integrity [23-29]. Heat is generated as a focused heat source such as a laser to sufficiently melt the surface of the substrate and creates a melt pool. A focused powder stream provides material for the melt pool using to form a raised portion of the material. The nozzle is moved over the substrate using a computer-controlled positioning system to create the desired geometry. This is illustrated in Figures 1 and 2 that depict the DMD process and laser motion, and the metal surface built across layers, respectively. Finite element method (FEM) analysis is a numerical approach for solving differential equations over complex geometries with broad applications in simulating structural properties and fluid dynamics. In this method, first the domain is discretized into small elements, and then a system of equations is assembled over all the elements [31-38]. GAMMA is a FEM frame- work that solves transient heat transfer equations for metal powder-based AM processes such as Directed Energy Deposition (DED) and Selective Laser Melting (SLM). Although an accurate thermal analysis of AM provides vital information for determining microstructure evolution and mechanical performance of the part, this kind of analysis can take weeks or months of computing time and therefore too computationally expensive for large-scale problems or optimization purposes [39-44]. For a given set of processing parameter inputs such as build geometry, laser power, and scan speed, GAMMA calculates spatially-dependent thermal histories within the part, such as temperature profiles and maximum cooling rate. In this work, we use GAMMA to generate the database to train our ensemble model. The idle pace of development and deployment of new/improved materials has been deemed as the main bottleneck in the innovation cycles of most emerging technologies. Exploring and harnessing the association between processing, structure, properties, and performance is a critical aspect of new materials exploration [45-51]. Data-driven techniques provide faster methods to know the important properties of materials and to predict feasibility to synthesize materials experimentally. This can expedite the research process for new materials development. Many initiatives to computationally assist materials discovery using ML techniques have been undertaken. There has been some limited work on the application of ML techniques for AM processes. Mozaffar et al. proposed a data-driven approach to predict the thermal behavior in a directed energy deposition process for various geometries using recurrent neural networks [52-60]. The proposed approach mapped the position of a point on the printing surface, the time of deposition, the distance of the closest cooling surface, and laser parameters with the thermal output. Baturynska et al. propounded a conceptual framework for combining FEM and ML methods for optimization of process parameters for powder bed fusion AM. Choy et al. designed a novel recurrent neural network architecture 3D recurrent reconstruction neural network (3D-R2N2) that learned mapping from images of objects to their underlying shapes in an AM simulation environment. Scime et al. developed supervised as well as unsupervised models for detecting irregularities and flaws on the laser bed during the AM process [64-71].

3.0 RESEARCH METHODOLOGY

The main idea of this research is the development of hybrid deep learning model for forecasting melt pool temperature during additive manufacturing process by exploiting the benefits of convolutional and long short-term memory networks. Convolutional networks are special kind of neural networks for processing grid-like topology, such as time series (1D) and images (2D). They have been effective for learning spatial information of time series. Whereas, LSTM networks are tremendously successful in identifying short and long-term dependencies. Thus, the proposed CNN-LSTM model for forecasting melt pool temperature combines the advantages of both CNN and LSTM networks. The hybrid model consists of two components: The first component consists of convolutional and pooling layers, in which features are developed from the internal representation of time series data, while the second component exploits the features generated by LSTM and dense layers. Each layer is briefly discussed in the following sections [67-71]. Figure 1 shows the 1D convolutional operation. Convolutional networks have advantages such as sparse interactions and weight sharing over multilayer perceptron networks. This effectively reduces the number of parameters used in model computation. The output s in Fig. 1 is the convolved output of three inputs, that is, the output is only affected by the kernel width. Control systems in manufacturing can be divided into two broad categories. The first class is error-based control systems in which changing parameters (parameters of manufacturing machine such as laser power, speed) are estimated and based on the error values from the experiment, the initial guess is corrected until the desired criteria is met [72-79]. The second class is model-based in which instead of estimating the initial value of machine parameters, they will be determined by a model. While an error based control system can be useful in many applications such as motion control, its application in AM process parameter control is not common because a significant deviation will ruin the part. Developing control manufacturing processes in a way to achieve desired properties in the final product is not a new attempt. It started from simple trial and errors and gradually developed to complicated multiple-layer feedback control systems to manipulate system settings for real-time control [1-18]. However, growing demand for controlling more and more detailed and complicated properties of products overpassed current science and many scientists tried to come up with new methods to overcome this challenge. As a data- driven methodology is more intuitive with a model-based system, our proposed approach outlines such a control system where the model is developed by training a machine learning algorithm. We explored across many regression algorithms for the developing our models including linear regression (ordinary least square), regularized linear regression: Lasso (L1- regularization) and Ridge (L2-regularization), boosted and bagged decision trees [19-27]. We did not consider neural networks for this framework. Although, a recurrent neural network model trained on temporal features can be combined with a feed-forward neural network trained on non-temporal features, training deep neural networks would take hours to train which is many order of magnitudes time more than the simulation time for FEMs and not feasible for a real-time prediction system where training has happened in-situ. Further, algorithms based on auto regression and moving average such as ARIM would not be able to capture spatial non-temporal relationships. This is also evident from our benchmarking experiment in Table I. We considered two metrics R^2 (coefficient of determination) and % MAE to evaluate the performance of the models. Algorithms using an ensemble of decision trees have achieved state of the art results for various machine learning tasks [28-36]. As a non-parametric method like decision trees performed better than parametric methods like linear regression, we decided to explore both boosting and bagging decision trees. Ensemble-based methods have been successful in tackling problems with sequential components. While AdaBoost and XGBoost are tree-based ensemble boosting algorithms in which each successive tree harnesses the decision made by the previous tree, bagged algorithms like Random Forest(RFs) and ERTs make a decision based on the average of many different trees. For both boosting and bagging, weak learners are utilized in the form of trees with limited depth. Boosting models are sequential learners and harnesses weak learners in sequence [37-43]. As bagged models use many weak tree-based learners in parallel, and hence can be parallelized in the order of the number of processors. As the time of training is essential for a real-time application, we choose bagged decision trees and in particular, ERTs as they outperform RFs for our experiments. Table I demonstrates the performance of all the different algorithms trained on the first 200 time steps for predicting the next 300 time steps. ERTs use an ensemble of decision trees in which a node split is selected completely randomly with respect to both variable index and variable splitting value [44-51]. ERTs are very good generalized learners and perform better in the presence of noisy features. As compared to RFs, ERTs decrease the variance and increase the bias by randomly selecting a node split independent of the splitting value. Both RFs and ERTs can utilize bootstrap aggregation wherein each weak learner builds a model based on a random sample of observations from the training data, with replacement [52-59]. Bootstrap aggregation helps in reducing variance in bagged ensembles. Researchers have proposed rolling recursive or iterative au- to regressive moving average modeling for time series pre- diction. In this work, we decided to explore iterative prediction based on ERTs as we have a combination of historical as well as spatiotemporal features [60-69]. We propose an iterative model in which an initial model is first developed based on the ground- truth data. Then, the data points predicted by the initial model is added to the ground-truth data to develop a model for the next stage, which predicts the temperature profile of voxels for future time-steps. We iteratively keep predicting future time- steps using predicted temperature profiles from the previous stage alongside ground-truth data. Figure 6 demonstrates the iterative learning process of our proposed model [70-79].

TABLE I

COMPARISON OF PERFORMANCE FOR DIFFERENT MACHINE LEARNING ALGORITHMS WITH CORRESPONDING R^2 AND % MAE BASED ON TRAINING ON THE FIRST 200 TIMESTEPS AND PREDICTING NEXT 300 TIMESTEPS. FOR EACH ALGORITHM, WE EXPLORE VARIOUS HYPERPARAMETERS AND PRESENT THE BEST MODEL.

Algorithm	R^2	**% MAE**	**Training Time (in seconds)**
Linear Regression	0.23	25.08	0.52
Lasso Regression	0.21	23.11	0.53
Ridge Regression	0.38	17.28	0.56
ARIMA	0.15	29.39	0.67
Decision Trees	0.76	9.74	2.30
AdaBoost (20 trees)	0.89	9.40	9.89
AdaBoost (50 trees)	0.92	6.45	55.27
AdaBoost (200 trees)	0.94	3.21	202.58
XGBoost (20 trees)	0.71	13.25	15.65
XGBoost (50 trees)	0.96	2.59	30.92
XGBoost (200 trees)	0.97	2.01	105.67
Random Forest (20 trees)	0.96	1.66	9.88
Random Forest (50 trees)	0.97	1.44	26.68
Extra Trees (20 trees)	**0.99**	**0.81**	7.25
Extra Trees (50 trees)	**0.99**	**0.21**	21.32

4.0 RESULT

In this section, we present the experimental settings and describe the results of the proposed system for predicting temperature profiles in an AM process. All experiments are carried out using NVIDIA DIGITS DevBox with a Core i7-5930K 6 Core 3.5GHz desktop processor, 64GB DDR4 RAM. The python VTK librarywas used for processing and converting the voxel data. The data preprocessing, as well as most of the regression models, were implemented using Scikit-Learn. The XGBoost package was utilized for creating the xgboost model. The ARIMA model was trained from the statsmodels package. For the iterative model, we performed extensive grid-search across various sizes of time step intervals and found the best results when the time step interval was equal to 20. For the experiments, we evaluate with different combinations and ratios of train and test splits. It is to be noted that instead of splitting the train and test set based on a fixed fraction, we divided the dataset based on the timesteps. For instance in Table II, we use data points up to 1000, 800, 500 and 300 timesteps for training and then we predict the next 200, 400, 700, and 900 timesteps respectively. For instance, when we use 800 timesteps for training and 400 for the test set, it corresponds to about 4.34 million training data points and 4.71 million test data points.

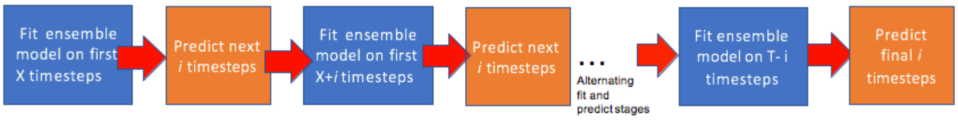

Fig. 4. The proposed model using ERTs to predict temperature profiles for additive manufacturing processes. It is to be noted that the number of data-points predicted at each step is not the same as the number of data-points for each voxel. This is because the model predicts not only the temperature of the newly created voxels but also the temperature of the same voxels presents in the training set at a later time-step.

TABLE II

COMPARISON OF COMBINATIONS OF TIME-STEPS USED FOR TRAINING AND TEST IN THE ITERATIVE MODEL (WITH CORRESPONDING R^2 AND % MAE). WE VARY THE NUMBER OF TIME-STEPS USED FOR TRAINING AND VALIDATION. THE TOTAL NUMBER OF TIME-STEPS - SUM OF THE TRAINING AND VALIDATION TIME-STEPS ARE ALWAYS EQUAL TO 1200.

Training		**Test**		R^2	**% MAE**
No. of timesteps	**No. of datapoints (in millions)**	**No. of timesteps**	**No. of datapoints (in millions)**		
1000	6.75	200	2.30	0.992	0.289
800	4.34	400	4.71	0.989	0.679
500	1.72	700	7.33	0.982	1.329
300	0.63	900	8.42	0.972	1.848

TABLE III

COMPARISON OF PROPOSED ITERATIVE MODEL WITH A DIRECT MODEL THAT DIRECTLY PREDICTS THE TEMPERATURE OF SUBSEQUENT POINTS. WE PRESENT THE TIME TAKEN AS WELL AS REGRESSION METRICS (CORRESPONDING R^2 AND % MAE) FOR BOTH THE MODELS. THE INITIAL NUMBER OF TIME-STEPS USED FOR TRAINING IS SET TO 200 AND THE SIZE OF THE ITERATION IS SET AS 20 TIME-STEPS. WE VARY THE NUMBER OF FUTURE TIME-STEPS PREDICTED.

Iterations	**Future Timesteps Predicted**	**Iterative Model**			**Standard Model**		
		Time (in seconds)	R^2	**% MAE**	Time (in seconds)	R^2	**% MAE**
10	200	68.69	0.989	0.675	0.293	0.921	5.39
20	400	137.08	0.978	1.444	0.308	0.906	5.71
30	600	210.04	0.976	1.489	0.317	0.876	6.07
40	800	278.61	0.971	1.903	0.480	0.861	6.55
50	1000	353.96	0.969	1.721	0.590	0.794	6.63

that directly predicts temperatures of future time steps varying between 200 to 1000. This experimental design of selecting training data based on time steps instead of layers also helps in generalizing the training set-up. For instance, the first 200 time steps would represent a few completed layers and an incomplete layer. The same intuition follows for the time steps in the test set. By training on different time steps allows us to generalize the framework to different shapes. Although the direct model is much faster, the iterative model performs much better than the direct model. For instance, while predicting the temperature for 1000 future time steps, the iterative model takes 353.96 seconds, the direct model requires 0.29 seconds. However, we can observe that the % MAE value of the direct model is much worse as compared to the iterative model. While the iterative model has R^2 between 0.97 and 0.99 and % MAE between 0.68 to 1.73 %, the direct model has R^2 between 0.79 and 0.92 and % MAE between 5.39 to 6.63 %. The results in Table IV illustrates that interior and edge (vertical) voxels comprise the bulk of the voxels (40.15% and 49.20%). This is anticipated as for any new layer created, none of the voxels in the new layer would have a vertical neighbor until a new layer is deposited. We also find that there is no significant difference in the prediction accuracy between the type of voxels. This demonstrates further that our iterative prediction model is able to learn the temperature profiles for both edge voxels as well as interior voxels.

TABLE IV
COMPARISON OF R^2 AND MEAN ABSOLUTE ERROR% ACROSS THE DIFFERENT TYPES OF VOXEL

Type of voxel	% of overall voxels	R^2	% MAE
Interior	40.15	0.990	0.916
Edge (Lateral)	4.92	0.992	0.898
Edge (Longitudinal)	5.09	0.988	0.923
Edge (Vertical)	49.20	0.989	0.918
Edge (Diagonal)	0.63	0.988	0.926

TABLE V
COMPARISON OF NUMBER OF TREES/ESTIMATORS IN THE ENSEMBLE. AS WE VARY THE NUMBER OF ESTIMATORS, WE PRESENT THE TRADE-OFF IN THE FORM OF TIME AND R^2 AND MEAN ABSOLUTE ERROR%. THE NUMBER OF VOXELS PREDICTED IN EACH ITERATION IS 25, AND THERE ARE 40 STEPS IN EACH ITERATION

No. of estimators	Overall Time (in seconds)	R^2	% MAE
4	154.5	0.964	2.14
10	257.5	0.970	1.38
20	493.2	0.975	1.29
50	902.4	0.981	1.03

5.0 CONCLUSIONS

This paper presents essential components of a scientific framework for a model-based real-time AM control system. The proposed approach utilizes extremely randomized trees - an ensemble of bagged decision trees as the regression algo- rithm iteratively using temperatures of prior voxels and laser information as inputs to predict temperatures of subsequent voxels and is able to achieve % MAE below 1% for predicting temperature profiles. One of the advantages of a real-time system is instead of training a prior model ahead of time, one can be trained in-situ. It is crucial for the versatility of the AM ML-driven simulation process, especially as factors such as laser path, laser speed, and laser temperature can largely influence the temperature profile. In the future, we plan to explore the impact of voxel mesh size on the prediction results across coarse to finer mesh. The next goal of this framework is to be part of an interleaved FEM-ML control system that harnesses the temperature profile of the odd layer (Layer i) calculated using FEM to predict the subsequent even layer (Layer $i + 1$). Layer $i + 2$ will then be calculated using FEM simulation, and Layer $i + 3$ will be predicted. This can accelerate the speed of simulations by nearly a factor of two, hopefully without impacting the accuracy significantly. Although this work restricts itself to temperature profile prediction for an AM process, the same idea can be extended to related manufacturing processes such as incremental forming [59]. In general, this work can be extended to any phenomenon which utilizes partial differentialequation based modeling.

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