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Application Of Artificial Intelligence For Temperature Profile Prediction In Additive Manufacturing Process

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Abstract. Additive manufacturing (AM) is the computer-aided design for the successive addition of layers by layer material. It is widely used because of the fast prototyping using laser metal deposition, which is difficult to implement using conventional techniques. Understanding the temperature profile prediction is necessary in AM processes, such as Bed Fusion process (PBF) technology to produce the right quality parts. Thus, the temperature profile prediction using Artificial intelligence techniques, like data-driven models and real-time iterative models using complex geometries, require real time control systems by considering the in-situ data. Besides, enhancing the accuracy of prediction is the hectic challenge faced by the existing systems. Hence, the proposed temperature profile prediction is developed based on an Artificial Intelligence method named Global herding algorithm-based neural network (global herding-based NN) to overcome the challenges associated with the existing methods. The proposed global herding optimization is developed by hybridizing the herding characteristics associated with the standard Elephant herding optimization (EHO) and Rhino Herd (RH) optimization to boost the solution's global optimal convergence. Moreover, the integration of the proposed global herding optimization with the NN model ensures the optimal selection of the hyper-parameters of the NN classifier, which renders effective performance of the temperature profile prediction. The effectiveness of the proposed model is revealed based on the performance metrics, such as MAE of 11.778, MAPE of 3.432, and MSE of 11.778.
Keywords: Energy Storage, Thermal Energy Storage, Latent Heat, Heat Transfer, Energy Efficiency.

1. Introduction

Additive manufacturing (AM) is the 3D digital design method used in the modern manufacturing process for the layer-by-layer deposition of the material [1] [2]. It is a tool used for the design of complex geometries easily by rapid prototyping and visualization besides, it is very flexible to design [3], and hence, AM is widely used in many applications, like assembling of the parts in aerospace, marine, medical, automobile and so on. The AM is categorized based on source of energy, material processed, deposition mechanism, and technologies [4]. The deposition of layer-by-layer material reduces the cost because it reduces the scrap rate, multi-step manufacturing, building density, and accurate shape. Moreover, the AM technique needs no tools or minimized tools for processing compared to the existing techniques for manufacturing [3]. In addition, AM has a reduced supply chain, material usage, energy usage and enhances innovative ideas [5]. The selective laser melting (SLM) is a technique of AM, which uses metal AM processing. It requires a high density of laser powder for the melting and fusing process of layer by layer metal deposition [6]. The metal-based AM is used enormously because of its ability to design complex geometries using the powder bed fusion (PBF) of metal AM [7]. Using this technique, the 3D model can also be designed by considering the faster heating process, melting, fluid flow, remelting of the previous layer, and cooling the metal deposition [1]. In the direct metal deposition of the AM, the metals like the Titanium or steel are used to deposition the product [8]. In the PBF method, the complex geometries were designed cost-efficiently, either in a single block or small batch. Although, in addition, AM is widely used in the manufacturing process and is an emerging technique, it also has some challenges like tensile residual stress, high thermal stress, steep temperature gradient, and so on. The AM with the multi-physics aspect is not applicable in all the physical techniques [3]. The heat produced during the repeated solidification leads to a huge thermal gradient, which produces cracks and porosity, partly distortion and stress. Hence there is a need for the heat monitoring and control technique in the AM. The embedded thermocouple technique helps to predict the temperature inside the substrate. Similarly, the infrared camera helps to predict the temperature on the surfaces [9]. Likewise, the metallographic method helps to predict the temperature by considering the microstructure of the solidification [8]. However, several existing techniques are devised to predict the temperature profile of the AM process, which has a high computational cost. Besides, the numerical models based on the finite element method (FEM) are developed, which has high distortion and residual stress. Above all, the machine learning approach has been applied to various areas, like strategies planning, optimization, and calls for integration with other fields [10]. This research aims to predict the temperature profile of the AM processing using the proposed global herding-based NN technique. The steps followed in the temperature profile prediction are data generation, pre-processing, and temperature profile prediction. Initially, the input data is readed, and the data required for the prediction is generated. Then, it is further pre-processed for the transformation of the data into the structured format. Finally, the temperature profile prediction is employed using the proposed global herding based-NN. The key contribution of the paper is given below: Proposed global herding algorithm: The global herding algorithm is developed by integrating the Elephant herding optimization (EHO) and Rhino Herd (RH) algorithm.The newly designed global herding algorithm is employed to train the NN, which predicts the temperature profile in AM process. The remaining sections of the paper are arranged as follows: Section 2 elaborates the description of the conventional AM processing utilized in literature and challenges faced, which are considered the inspiration for developing the proposed technique. Then, the proposed temperature profile prediction technique is described in section 3, and results and discussion is portrayed in Section 4. Finally, Section 5 present the conclusion.

2. Motivation

Generally, AM processing is an essential manufacturing field because instead of removing the material, it works by adding extra layers by material deposition. Therefore, the cost required for this prototyping is very lower, and the material's wastage can also be minimized. In this section, conventional temperature profile prediction techniques are analyzed, and several challenges faced by those techniques are considered as a motivation for developing a novel temperature profile prediction in AM processing method. Literature Review:The literature review of the existing methods for the temperature profile prediction in AM is reviewed. The pros and the cons are detailed in this section. Arindam et al. [1] devised a temperature profile prediction in the additive manufacturing process. The regression algorithm named randomized trees iteratively uses the input from the temperatures of prior voxels and laser information. They achieved the mean absolute percentage error (MAPE) of less than 1%; hence it can be used in the real time application models. However, the developed method fails to use the voxel mesh size to predict the temperature profile. Roy, M. and Wodo, O [11] devised an additive manufacturing process using the data-driven approach. The features are extracted from the input gcode and are used as the input for the surrogate model (SM) for the temperature prediction. The performance of the developed method is evaluated based on the reduced storage and the computational cost. Besides, they achieved better accuracy than the other state-of-the-art techniques, and the devised system is faster in predicting the temperature profile. However, the developed method is not applicable for complex geometrics. Ren, K., et al. [10] devised a thermal prediction based on physics-machine learning. In this, RNN-DNN is employed for the thermal evaluation of laser aided AM (LAAM). Besides, the finite element is used for the continuous prediction of the temperature. They achieved better prediction accuracy but failed to evaluate its performance using the multi-layer 3D decomposition model. Elham et al. [4] devised an AM using elastoplastic hardening. In this, the thermo-mechanical analytic model is used for the prediction of in-built thermal stress. The simulation is performed by evaluating the finite element for the validation of elastoplastic hardening. The prediction result obtained is faster and more accurate. The developed method uses the additional methods for validating the models is the drawback of the system.

Challenges

1. The temperature profile prediction is employed in [1] using the machine learning technique based on a real-time iterative approach. However, the extent of the mesh size of the voxel is not explained clearly and the prediction accuracy needs to be focused.
2. The AM technique with the data-driven model [11] is not applicable for complex geometries.
3. The LAAM devised in [10] faces a major challenge as it cannot perform thermal prediction on multilayered 3D deposition materials.
4. The Thermo-mechanical modeling of thermal stress devised in [4] can't predict the stress within the developed model. Besides, it requires additional design for the validation of the developed method.

3. Proposed Methodology of Temperature Profile Prediction Using the Artificial Intelligence

The temperature profile prediction is employed using the proposed global herding-based-NN method. The temperature profile prediction of the AM process is employed using three steps: data generation, pre-processing of the data, and finally, the temperature profile prediction using the proposed global herding based-NN technique. Figure 1 shows the block diagram of the proposed Global herding- based NN for temperature profile prediction. Initially, the input data is taken from the database for the data generated using the GAMMA technique, which provides the heat flux and temperature for every step and every process of AM processing. Then, the pre-processing is devised for the transformation of the data into the structured format. Finally, the temperature profile prediction is employed using the Global herding based-NN, which is trained using the proposed global herding algorithm. The global herding algorithm integrates the elephant herding optimization [12] algorithm ad the rhino herding [13] algorithm. As a result, the newly developed temperature profile prediction technique provides the most accurate prediction.

Data Generation: The data required for the temperature prediction method is devised using the Generalized Analysis for Multiscale Multi-Physics Application (GAMMA), which is used to solve the time-related temperature equations. It is helpful to obtain the temperature and its flux evaluation for all the elements in each step of the manufacturing process. In the simulation of the GAMMA FEM, the cuboidal shape FEM is assumed with the dimension of 20 mm x 20mm x 3mm size. The edge length of the mesh voxel is 0.5mm for the finely coarse material, which stands for voxels in axis. Hence, this research employs a total of 9600 voxels, and the simulation time for performing the FEM analysis is restricted to an hour. However, the simulation time increases with the reduction of the mesh size. For each step, the mesh size varies because the simulation follows the motion of the laser and generates one voxel from the data points, where stands for the total data points generated during the first voxel establishment and stands for the data points generated during the second establishment. Thus, a total of data points are established. Finally, the total data points generated is represented as.

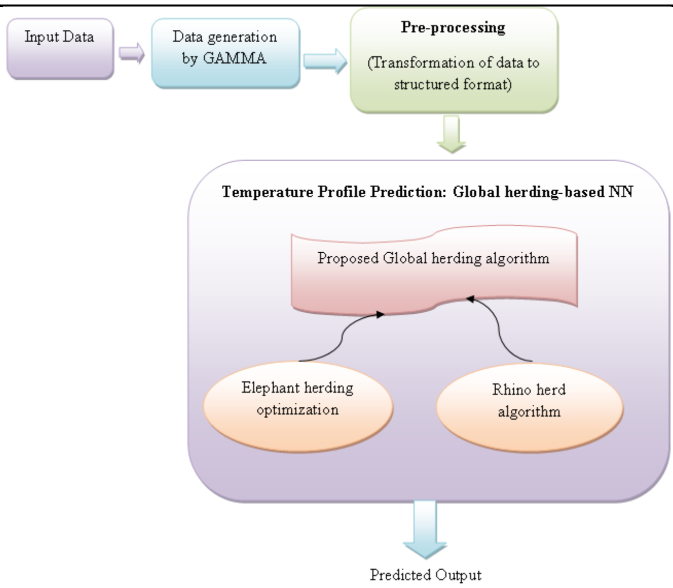


FIGURE 1. Block diagram of the proposed Global herding- based NN for temperature profile prediction

Pre-processing of the generated data: The temperature profile of the AM process keeps on increasing, like crest and tough manner. The tough represents the slower cooling process of the direct metal deposition (DMD), while the crest is the heat generation by the neighbor voxel. Thus, the temperature profile depends on several factors, such as spatiotemporal features, the total time elapsed after generating the voxel, and the voxel position. However, since the temperature is dynamic between cooling and heating, spatiotemporal features employed for training the prediction model remain insufficient. Hence, the following features are considered for establishing the training model based on the proposed NN classifier to which the input vector is accomplished with the following features.Spatial features: The current voxel's coordinates concerning the laser's current position. Temporal features: It is the time required for the voxel generation and its elapsed time.Spatiotemporal features: It is the temperature of the nearby voxels at the time .Historical features: The temperature profile generated during the time to .The tool speed and its path represent the current position of the laser. In addition, if any of the temperature profile is missed, it is replaced by the dummy value -99. The proposed method predicts the temperature profile of the AM processing using the training data.

Categories of voxel:The voxel categories are classified into 5 types based on the spatial features because the temperature profile also depends on the nearby voxels. Therefore, it is detailed as: (i)Interior: It has all the nearby voxels. (ii) Edge (Lateral): It refers to the missing of the nearby voxel in the . (iii) Edge (Vertical): It refers to the missing of the nearby voxel in the . (iv) Edge (Longitudinal): It refers to the missing of the nearby voxel in the . (v) Edge (Diagonal): The voxel missing in the diagonal or the planar, other than the above three voxels is referred as edge diagonal category. Temperature profile Prediction using the proposed global herding-based NN classifier:The temperature profile prediction of the AM processing is performed using the proposed global herding-based NN classifier. The optimal hyperparameters of the NN classifier are tuned by the proposed global herding algorithm, which boosts the performance of prediction.

Training the NN using the proposed Global herding algorithm:The parameters of the NN are tuned by using the proposed global herding algorithm, which is developed through hybridizing the herding characteristics from the standard EHO [12] and RH [13] algorithm to boost the local optimal convergence avoidance phenomenon. The EHO is inspired by the herding behavior of the elephants, in which a matriarch heads it. The female elephants live with their families, and the male elephant leaves the family and lives independently by gradually leaving the family. Similarly, the RH is a swarm-based algorithm in which the synoptic model is used to evaluate space use. By integrating both the algorithm, efficient global optimization is achieved by a fast convergence rate. Besides, it is used to solve the optimization problems effectively by the avoidance of the local minima. Hence by using this overall performance of the system is enhanced.The global-herding algorithm follows two model namely synoptic model for the updation of the space use and the synoptic model for the direction. The synoptic model avoids the environmental covariates; instead it uses the null technique for the explanation of the distribution of the space. The algorithmic steps for the proposed global herding algorithm are detailed below: Population initialization:The first step is the population initialization, in which the parameters null model is modeled as,

$$(1)\quad a_o(m) = \frac{2}{d^2 \pi b^2 \Gamma(d)} \exp\left[-\left(\frac{\|m-\mu\|}{b} \right)^{2/d} \right]$$

where, refers to the gamma function and is referred as the distribution center. The shape parameter is referred as, , the scaling parameter is referred as, , assumed that both the scaling and shape parameter be greater than zero and the distance between the center of the distribution and the location of the rhino is represented as, Fitness evaluation: The fitness function is used to find the best solution for the optimization problem such that the measure used to find the fitness value is expressed as,

$$(2)\ MSE = \frac{1}{n}\sum_{i=1}^{n}(X_i - \hat{X}_i)^2$$

where, is the total sample is the predicted output, is the actual output. Solution update for deriving the best solutions: The synoptic model neglects the environmental covariates; hence the function is added to represent the environmental covariates. The probability distribution density of the searching space of the rhino is represented as, . Hence, the synoptic model with environmental covariates may be modeled as,

$$(3)\ P(m) = \frac{a_o(m) + \alpha \times R(m) \times a_o(m)}{\int [a_o(m) + \alpha \times R(m) \times a_o(m)]dm}$$

Where, the parameter is referred to as the controlling parameter to handle the magnitude. The synoptic model after introducing the environmental covariates is expressed as,

$$(4)\ P(m) = \frac{a_o(m)\Pi_{l=1}^{k}(1 + \alpha_l \times R_l(m))}{\int [a_o(m)\Pi_{l=1}^{k}(1 + \alpha_l + R_l(m)))dm}$$

The update equation of the synoptic model for the nth environmental covariates of lth rhino with the area comprised of grid cells is expressed as,

$$(5)\ P(M_{l,n}) = \frac{a_o(M_l)[1 + \beta_l \times R_l(M_{l,n})]}{S\sum_{k=1}^{x}[a_o(M_{l,k})[1 + \alpha_k \times R_k(M_{l,k})]]}$$

where, the population is referred as, are the controlling parameter concerning the environmental covariates. The update equation of the elephant depends on the matriarch and is expressed as,

$$(6)\ P_{new,h_m,n} = P_{h_m,n} + a \times (P_{best,h_m} - P_{h_m,n}) \times b$$

where, is the update equation of elephant in clan, are the random number varies from is the old position of the elephant and is the best solution. Integrated update equation:

$$(7)\ P_{l,m} = 0.5P(M_{l,n}) + 0.5P_{new,h_m,n}$$

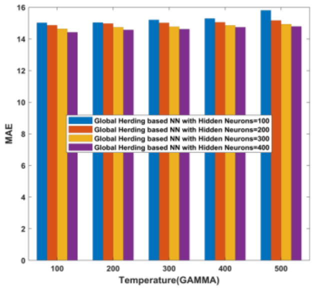
The integrated equation based on [14] is represented as,

$$(8)\ P_{l,m} = 0.5\left[\frac{a_o(M_l)[1 + \beta_l \times R_l(M_{l,n})]}{S\sum_{k=1}^{x}[a_o(M_{l,k})[1 + \alpha_k \times R_k(M_{l,k})]]}\right] + 0.5[P_{h_m,n} + a \times (P_{best,h_m} - P_{h_m,n}) \times b]$$

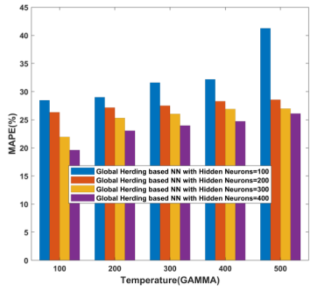
The updated equation (8) is the final update equation of the proposed global herding algorithm. Re-evaluation of the Fitness measure: After updating the position, the fitness value is re-evaluated to find the feasibility of the solution, and the best fitness value is accepted as the optimal solution. Termination: The steps (2) to (4) are repeated until the best solution is attained.

4. Result and Discussion

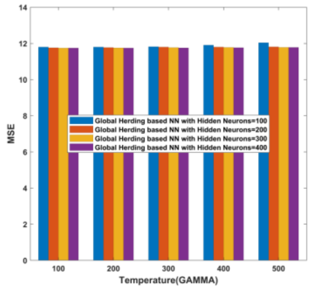
This section describes the results and discussion of the proposed global herding based-NN for the temperature profile prediction concerning the performance measures. Experimental setup:The implementation is done in PYTHON, and the comparative analysis of the proposed model concerning the existing models is done based on the metrics, such as mean square error (MSE), mean absolute scaled error (MASE), and mean average error (MAE). The comparative methods employed for the analysis of the proposed method are Surrogate Model (SM) [11], RNN–DNN thermal analysis model [10], and the closed-form solution model [6]. Performance metrics:MASE: It is the mean absolute scaled error used to measure the accuracy of the forecast. It is expressed as, (9)MSE: The average square difference between the estimated values and the actual result. It is expressed in equation (2)MAE: It is also the difference between the actual and estimated value and is expressed as, (10)Where, is the total sample is the predicted output, is the actual output. Performance Analysis: Figure 2 illustrates the performance analysis of the proposed method by varying the hidden neurons using the performance metrics like MAE, MAPE, and MSE. The analysis by considering the performance metric MAE is depicted in figure 2 (a). When the temperature is 100, the MAE evaluated by the proposed Global herding based NN with 100, 200, 300, and 400 hidden neurons is 12.383, 11.907, 11.750, and 2.936. The analysis by considering the performance metric MAPE is depicted in figure 2 (b). When the temperature is 200, the MAPE evaluated by the proposed Global herding based NN with 100, 200, 300, and 400 hidden neurons are 3.568, 3.523, 3.438, and 2.324, respectively. The analysis by considering the performance metric MSE is depicted in figure 2 (c). When the temperature is 300, the MSE evaluated by the proposed Global herding based NN with 100, 200, 300, and 400 hidden neurons is 12.431, 11.993, 11.777, and 4.893.



(a)



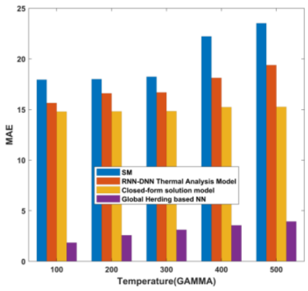
(b)



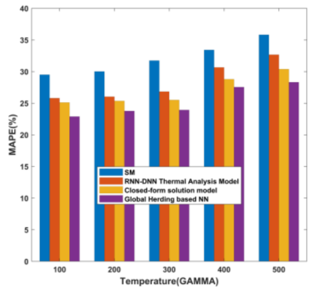
(c)

FIGURE 2. Performance analysis of the proposed method by varying the hidden neurons (a) MAE, (b) MAPE, (c) MSE

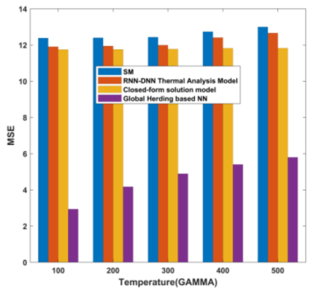
Comparative Analysis: The comparative analysis of the proposed Global herding based NN for the temperature profile prediction is evaluated by comparing it with the existing system like SM, RNN–DNN thermal analysis model, and closed-form solution model. The comparative analysis is evaluated in terms of MAE, MAPE, MSE, and RMSE and is depicted in figure 3. Figure 3 a) illustrates the comparative analysis by considering the MAE. When the temperature is 100, the MAE evaluated by the proposed and the existing methods like SM, RNN–DNN thermal analysis model, closed-form solution model, and proposed Global herding based NN are 11.798, 11.759, 11.746, and 11.744, respectively. Figure 3 b) illustrates the comparative analysis by considering the MAPE. When the temperature is 200, the MAPE evaluated by the proposed and the existing methods like SM, RNN–DNN thermal analysis model, closed-form solution model, and proposed Global herding based NN are 3.470, 3.437, 3.432, and 3.432, respectively. Figure 3 c) illustrates the comparative analysis by considering the MSE. When the temperature is 400, the MSE evaluated by the proposed and the existing methods like SM, RNN–DNN thermal analysis model, closed-form solution model and proposed Global herding based NN are 11.907, 11.800, 11.779, and 11.764, respectively.



(a)



(b)



(c)

FIGURE 3. Comparative analysis of the proposed method by varying the temperature (a) MAE, (b) MAPE, and (c) MSE

Comparative Discussion:Table 1 shows the comparative discussion of the proposed method with the existing techniques for the temperature profile prediction of AM process in terms of MAE, MAPE, and MSE. The MAE evaluated by the SM, RNN–DNN thermal analysis model, closed-form solution model, and proposed Global herding based NN are 12.039, 11.810, 11.782, and 11.778, respectively. The MAPE evaluated by the SM, RNN–DNN thermal analysis model, closed-form solution model and proposed Global herding based NN are 3.470, 3.437, 3.432, and 3.432, respectively. The MSE evaluated by the SM, RNN–DNN thermal analysis model, closed-form solution model and proposed Global herding based NN are 12.04, 11.81, 11.78, and 11.78, respectively.

TABLE 1. Comparative Discussion

Methods/ Metrics	**SM**	**RNN–DNN thermal analysis model**	**closed-form solution model**	**Proposed Global herding based NN**
MAE	12.039	11.810	11.782	11.778
MAPE	3.470	3.437	3.432	3.432
MSE	12.04	11.81	11.78	11.78

5. Conclusions

In this research, an iterative AI-based model is proposed for predicting the data points of the voxels, which in turn predicts the temperature profile of the data points. To predict the data points of the voxels, a ground truth table is utilized, which develops the initial model, which is an elementary model in prediction. The next model for predicting the temperature profile of the voxels in successive time-steps is evolved by integrating the data points predicted by the initial model with the ground truth table. Furthermore, the temperature profiles in the upcoming time steps are obtained from the predicted temperature profiles and ground truth data of the previous stages. The predicted data points at each iterative step will not be similar to that of the data points predicted for each voxel because the new voxels are predicted, and the temperature of the voxels in the training set are predicted. The experimentation of the proposed method is done in PYTHON and the proposed method is compared with the existing methods. The results show that the proposed method outperforms the other methods in terms of the metrics, such as MAE of 11.778, MAPE of 3.432, and MSE of 11.778. In the future, a new optimization technique is devised, and the prediction is employed using deep learning techniques to improve the prediction accuracy.

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