Machine learning model improvement based on additive manufacturing process for melt pool warmth predicting

Ladson Newiduom, Utian Junta, Akaw Johnima, Ibrina Browndi
Department of Urban and Regional Planning, Rivers State University, Port Harcourt, Nigeria

ABSTRACT

Melt pool temperature contains abundant information on metallurgical and mechanical aspects of products produced by additive manufacturing. Forecasting melt pool temperature profile during a process can help in reducing microstructural porosity and residual stresses. Although analytical and numerical models were reported, the performance of these are questionable when applied in real-time. Hence, we developed data-driven models to address this challenge, for continuous forecasting layer-wise melt pool temperature using a hybrid deep learning technique. The melt pool temperature forecasting by the proposed CNN-LSTM model is found to be better than other benchmark models in terms of accuracy and efficiency. The model results have shown that combining CNN and LSTM networks can extract the spatial and temporal information from the melt pool temperature data. Further, the proposed model results are compared with existing statistical and machine learning models. The performance measures of the proposed CNN-LSTM model indicate a greater potential for in-situ monitoring of additive manufacturing process.

KEYWORDS: Deep Learning, Statistical Learning, Machine Learning, CNN, LSTM.

1.0 INTRODUCTION

Metal additive manufacturing (AM) processes of directed energy deposition (DED) offer numerous possibilities for producing complex parts in aerospace and automotive industries without design constraints. Compared to traditional manufacturing, AM offers four key advantages that include design flexibility, sustainability, higher accuracy and efficiency, and faster production cycles. In recent years, AM techniques have brought key transformations in aerospace and automotive industries. For example, Boeing used more than 600 additively manufactured parts in its aircraft 777X. The BMW Group has produced over 300,000 additively manufactured parts in just one year [1-13]. Wire arc additive manufacturing also known as DED-arc produces near net-shaped parts by melting wire feedstock with an electric arc. The electric arc heat source has many processing advantages over other heat sources such as electron beam and laser. Plasma arc-based AM techniques offer wide ranges of power densities and metal deposition rates with high efficiency and flexibility. Cold metal transfer (CMT), which is an arc welding technology has shown significant potential in metal additive manufacturing of components. CMT is a relatively new technique that is characterized by many advantages including low thermal heat input and high deposition rates [14-26]. A substantial amount of research was reported on application of CMT for additive manufacturing in recent times. The effects of various arc modes in CMT process on porosity was reported. Fang et al. studied the evolution of microstructures and mechanical behavior of aluminum alloys. Ryan et al. studied the influence of build parameters and wire batch on porosity of CMT based additively manufactured aluminum alloy. There are still some critical challenges such as porosity and voids, particularly for producing parts with aluminum (Al) alloys, that need to be addressed before AM technologies take up widespread adoption in the manufacturing sector. The possible causes of microstructural defects are the lack of fusion, insufficient heat, entrapped gases and rapid solidification [27-38]. Investigating melt pool temperature profile such as temperature distribution and heat flow mechanism reveals information on most of the possible causes of microstructural defects. The melt pool temperature profile contains abundant information and that can be used to reduce the porosity defects and voids of the Al parts manufactured by AM. The melt pool in wire-arc additive manufacturing (WAAM) refers to the vicinity of electric arc and molten material interface where the wire feed stock is melted and form spherical molten metal droplet. Temperature variations can significantly affect the evolution of porosity in final products. In comparison to powder-bed AM, very few reports are available on WAAM that discuss the process parametric effects and melt pool temperature variations on porosity formation. This is due to the complex and dynamic nature of arc [39-47]. The metal deposition using an electric arc imposes thermal cycles not only on solidified material and substrate, but also on the previous deposited layers. The imposed thermal cycles result in partial melting of previous layers below the deposited layer, up to 4 layers, creating non-isothermal heat treatment. This heat effect leads to expansion and contraction of deposited metal and subsequent generation of residual stresses in the deposited structures. Also, the nucleation and dissolution of eutectic phases of alloys during solidification and melting processes, resulted in the formation of pores. The degree of residual stresses and porosity is a function of temperature distribution and thermo physical properties. Therefore, melt pool temperature monitoring and controlling helps in achieving desired microstructural and mechanical properties of the WAAM components [48-56]. This study aims to develop data-driven models for continuous forecasting of layer-wise melt pool temperature in order to control the microstructural defects. The temperature profile in the melt pool can be monitored using various types of sensors, such as pyrometers, thermocouples and infrared (IR) radiation. Thermocouples have limitations in being used for in-process monitoring, as they need contact with the parts to monitor temperature [57-68]. However, IR cameras and pyrometers are feasible for monitoring temperature of a process without contact. With the recent advancements in instrumentation, IR cameras are capable of obtaining temperature data with a sampling rate up to 100kHz. The temperature profile during DED processes have been extensively studied with regard to physics involved and data – based models. Physics-based models can be broadly categorized into numerical and analytical methods [69-77]. Analytical temperature models of DED involve solving of closed form welding heat transfer equations using boundary conditions. Cadiou et al. proposed a 3D heat transfer model for wire-arc additive manufacturing process The major limitations of analytical models are their general applicability and failure to address the uncertainties of thermo physical properties. Finite element method (FEM) is a numerical method of modelling of temperature profile. The accuracy of these models is questionable due to the lack of process knowledge [78-85]. Also, the performance of numeral models depend highly on boundary conditions, element types and meshing schemes. In contrast to physics-based models, data driven models offer many advantages and can model highly non-linear processes such as melt pool formation with good accuracy and efficiency. Further, data-driven models require only limited knowledge of process and physics involved. Some studies were reported on defect detection from melt pool temperature profile during DED process by using classical machine learning and deep learning techniques [1-7]. Recently, a study was performed on prediction of melt pool temperature during DED process using machine learning. However, there are very few papers reported on controlling and monitoring of temperature profile during DED process. This research gap can be effectively addressed using deep learning time series forecasting techniques. The main idea is that deep learning time series models can forecast layer-wise melt pool temperature during DED process with higher accuracy and faster response times. In most of the time series data, correlations exist between observations [8-14]. A standard neural network considers all the observations as independent, that leads to an erroneous inference. With recent developments in deep learning techniques, many special types of neural networks have been introduced to deal with noisy and correlated time-series data and can lead to more accurate forecasting. Though some ARIMA family models can address the correlations in time series, they do not consider the effects of spatial dependencies. Traditional time series models such as ARIMA and SARIMAX works well when seasonal and trend components are known [15-21]. However, in real-time manufacturing, both seasonal and trend components change with regard to process parametric variations. These parameters need to be changed for each simulation when using traditional time series models. Among various deep learning techniques, convolutional neural networks (CNN) and recurrent neural networks (RNN) are most popular, efficient and widely used neural networks. Long short-term memory (LSTM) networks are special type of RNN that deals with long-term sequential dependencies very effectively. CNNs are traditionally used for image classification and recognition and do not account for sequential dependencies [22-29]. However, when dealing with time-series data, the main advantage of CNN is dilated convolutions. The CNN allows neural network to extract relationships between different observations in time series that accounts for spatial dependencies. Therefore, combining the CNN and LSTM models to exploit the benefits of spatial and temporal information of time series could improve the forecasting performance. In this paper, a hybrid deep learning model is proposed to forecast the layer-wise melt pool temperature during DED process. The proposed CNN-LSTM model performance is evaluated using RMSE, MAE and MAPE, and also compared the performance metrics with traditional statistical, machine learning and deep learning models [30-37].

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. 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 [1-16]. 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. 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 [27-24]. Mireles et al. proposed in-situ monitoring technique for defect detection. 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. Analytical models of temperature distributions of wire-based DED have been extensively studied in literature [38-44]. 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. 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 [45-51]. 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. 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 [52-58]. 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. 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 [59-66]. 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. 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 [67-74]. 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 [40]. Rehman et al. improved the accuracy of movie reviews sentiment analysis. A considerable amount of research has been conducted in the field of natural language processing using CNN-LSTM networks [75-82]. 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 [79-85].

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 [1-17]. 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 [8-27]. Each layer is briefly discussed in the following sections. 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 [28-37].

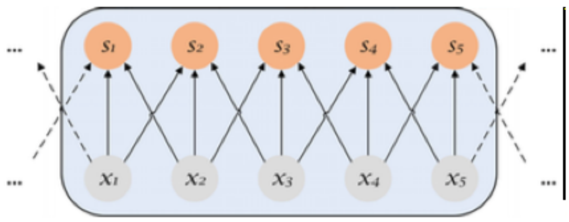

FIGURE 1. Schematic of 1D convolutional operation: s is formed with kernel size of 3.

The CNN layer receives step-wise melt pool temperature variables as inputs. The inputs must be represented in a structured matrix form, since the technique is originally developed for grid-like topologies. The convolutional filter consists of coefficient values in a matrix form and can be considered as a tiny window. This window slides through input matrix performing convolution operation. The output layer of CNN provides extracted feature information to several hidden layers and LSTM network. Each hidden layer of CNN consists of an activation, convolution and pooling layers respectively. Convolution layer performs convolution operation on an input sequence [38-46]. This operation reduces the number of parameters and leads to a deeper CNN-LSTM network. If xi, where i = 1, 2, ..., n is the input vector of melt pool temperature steps and n is the normalized unit window, then the resultant output vector, yij of the lth convolutional layer is as follows [47-58].

$$y_{ij}^{l} = \sigma\left(b_j^l + \sum_{m=1}^{M} w_{m,j}^{l} x_{i+m-1,j}\right) \qquad (1)$$

where σ is the activation function, blj is the bias for jth feature map, w is the kernel weight, and m is the index value of filter. The output of each neuron cluster is mapped to the next layer by pooling operation. This helps in reducing the number of computational parameters and cost. The pooling layers produce summarized values of the convolved features. The max-pooling for predicting melt pool temperature utilizes the maximum value of a convolved matrix, which adjusts over fitting issue also. The max pooling layer operation is represented in Eq. (2), where T is the stride and R is the size of pooling. The equation performs pooling operation on the previous convolutional layer [59-68].

$$p_{ij}^{l} = max_{r \in R}\left(y_{i \times T+r,j}^{l}\right) \quad (2)$$

LSTMs are a special kind of artificial RNN architecture that are capable of learning long-term dependencies of a time-series data. The issue in long-term memory of traditional RNNs was successfully addressed by LSTMs for sequential data. The hidden layers of these models employ cyclic connections which store useful information from previous states. Further, LSTM networks effectively tackle vanishing gradient problem of RNNs by storing useful information and discarding unnecessary information. Thus, LSTM networks provide better performance over classical RNN models. The LSTM layer of CNN-LSTM network stores the important information of melt pool temperature distribution that is extracted by the CNN layer. The output of LSTM layers is the resultant of consolidated memory units by storing long-term memory of previous hidden states. These memory cell units are able to extract and analyze temporal information of sequential data. The output information of CNN layer is fed to the gated units of LSTM network. For forecasting melt pool temperature time-series data, LSTM networks are well suited, by addressing the vanishing and explosive gradient problems that occur in traditional recurrent neural networks [69-76].

$$i_t = \sigma\left(W_{pi}p_t + W_{hi}h_{t-1} + W_{ci} * c_{t-1} + b_i\right) \quad (3)$$
$$f_t = \sigma\left(W_{pf}p_t + W_{hf}h_{t-1} + W_{cf} * c_{t-1} + b_f\right) \quad (4)$$
$$o_t = \sigma\left(W_{po}p_t + W_{ho}h_{t-1} + W_{co} * c_t + b_o\right) \quad (5)$$

The three-gate unit mechanism shown in Fig. 2, represents the working of each memory cell at a particular run. The gate unit is a combination of input, forget and output gate. The input gate along with control gate ct , controls the information that has to be stored in the memory cells at given time t. The forget gate ft controls the previous intervals information and decides which information has to be kept on memory cell, while output gate ot decides which information could be used for the memory cell output. Equations. (3) – (5) describes the operation of a LSTM unit [51-64].

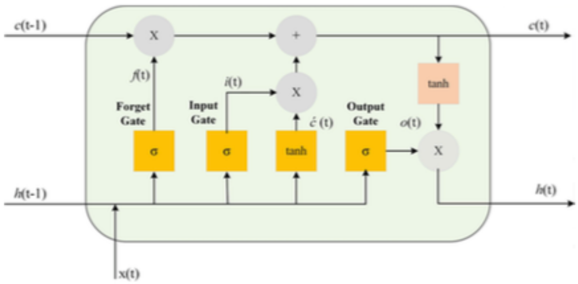

FIGURE 2. **LSTM network structure.**

Equations (6) and (7) provides the cell and hidden (ht) states derived from the input, forget and output gates. σ is an activation function, and W and b represents weight matrix and their associated biases. The output, pt of pooling layer at time t contains crucial information of melt pool temperature time-series data and passed to an LSTM cell [38-51].

$$c_t = f_t * c_{t-1} + i_t * \sigma\left(W_{pc}p_t + W_{hc}h_{t-1} + b_c\right) \quad (6)$$
$$h_t = o_t * \sigma(c_t) \quad (7)$$

The output of LSTM layer is fed to the fully connected layer. This can be used to generate melt pool temperature forecasting over a certain interval of time. Here, we fore- casted the melt pool temperature for the final layer while producing thin-wall structures. The proposed CNN-LSTM architecture is shown in Fig. 3. The input of the network is melt-pool temperature measurements for nine layers of deposition. The output of the network is forecasted values of melt pool temperature for 10th layer. The network in convolution and pooling layer consists of two Conv1D layers, two max-pooling layers and one time-distributed layer. Subsequently, features extracted from the convolutional layer is passed through LSTM layer, followed by dense layers. Rectified Linear unit (ReLu) is used as an activation function for convolutional layers. Though there are other modified activation functions, ReLu shown to be effective for melt pool temperature forecasting with no sign of exploding or vanishing gradient problems. To avoid over fitting during training, dropout was used. Dropout is a widely used technique to avoid over fitting that randomly ignores the neurons during training phase. Further, number of epochs was carefully selected to avoid over fitting and same number of epochs were used for each sample. The design parameters of CNN-LSTM model are shown in Table 1. This table provides the information on number of filters used, kernel width, stride window and the number of parameters for each layer [72-85].

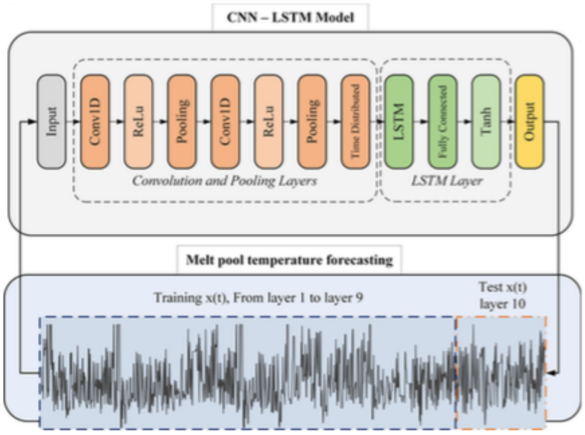

FIGURE 3. The architecture of proposed CNN-LSTM network.

The complexity of CNN-LSTM can be calculated by calculating the time complexities of the convolutional lay- ers and the LSTM layer individually. The complexity of CNN layer is estimated as O(dl=1 nl−1.s2l .nl.q2l), where d, nl−1, sl and ql are the number of convolutional layers, number of filters in lth layer, spatial size of filter and spatial size of output feature map respectively [48]. The complexity of the convolution layer grows quadratic ally with kernel width, number of kernels and cache unfriendly memory access [49]. Whereas, input length does not affect storage requirements of LSTM network, local in space and time [50]. Thus, the overall complexity of LSTM network is O(ω), where ω corresponds to number of weights. Therefore, overall complexity of CNN-LSTM network is the sum of complexities of CNN and LSTM layers and can be expressed as: O (dl=1(nl−1.s2l.nl.q2l)+ω).i.e ,where I is the length of input and e is the number of epochs [31-49].

TABLE 1. The proposed CNN-LSTM architecture.

Type	Kernel Size	Stride	Params #
Convolution (filters=64)	(3,1)	1	256
Activation (ReLu)	-	-	0
Max Pooling	(2,1)	2	0
Convolution (filters=64)	(3,1)	1	12352
Activation (ReLu)	-	-	0
Max Pooling	(2,1)	2	0
Time Distributed	-	-	0
LSTM (nodes=100)	-	-	142800
Activation (Tanh)	-	-	0
Dense (100)	-	-	10100
Dense (1)	-	-	101
Total number of parameters	-	-	165609

4.0 RESULT

Thin-walled structures are produced with aluminum alloy 4043/AA4043 wire with diameter of 2 mm and melting temperature is in range of 573◦ C and 632◦ C. The material is deposited on aluminum alloy 6061/AA6061 substrates. Nominal chemical compositions of AA6061 and AA4043 used in this study are shown in Table 1. Thin-walled structures were produced using a CMT 7000 VR power source. Fig.

3 illustrates the schematic of directed energy deposition platform used in this study. The wire feedstock was thoroughly cleaned and dried before experimentation. The substrate was firmly clamped onto the workbench and movement of welding torch in X and Y directions was controlled by a linear actuation system. The wire is deposited in single pass layers along the Z direction and the alternating layers are deposited in the opposite direction. A total of nine samples were produced by varying current and speed levels in order to collect the temperature data. Other parameters were maintained constant Table 2 shows the process parametric levels used in this study. Each parameter has three levels and a sample of thin-walled structure has ten layers in total. The length, height and width of each sample are 80 ± 2 mm, 30 ± 2 mm and 3 ± 0.5 mm respectively.

TABLE 2. Nominal chemical composition of materials used in this study.

Material	Al (%)	Si (%)	Mg (%)	Cu (%)	Fe (%)	Mn (%)	Zn (%)
AA6061	97.59	0.890	0.86	0.29	0.33	0.025	0.007
AA4043	93.05	6.0	0.05	-	0.8	-	0.10

where xi and x̅i are the actual and forecasted values of melt pool temperature ranging from i = 1,2, 3,...,N. The performance metrics of various statistical, machine learning and deep learning models are summarized. The performance measures of proposed CNN-LSTM algorithm for all the experiments are provided The metrics for experiments with various process parameters remains almost same. This shows the model's good repeatability characteristics for forecasting melt pool temperature in wire arc additive manufacturing process. Research shows the comparative plots of forecasted melt pool temperature values with actual values. All the forecasts are made for the roof layer (layer 10). The model exhibits robustness against noises. The average RMSE, MAE and MAPE of proposed CNN-LSTM model for sample 1 are 95.16, 75.43 and 12.19% respectively.

$$RMSE = \left[\frac{1}{N}\sum_{i=1}^{N}(\bar{x}_i - x_i)^2\right]^{1/2} \quad (8)$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|\bar{x}_i - x_i| \quad (9)$$

$$MAPE = 100 \times \frac{1}{N}\sum_{i=1}^{N}\frac{|\bar{x}_i - x_i|}{x_i} \quad (10)$$

5.0 CONCLUSIONS

The proposed CNN-LSTM network for forecasting melt pool temperature during additive manufacturing process is found to be an effective and competitive technique for online monitoring of process. The existing methods for online monitoring mostly used defect detection techniques such as x-ray, computed tomography measurements that are mapped with temperature profile to adjust process parameters. However, temperature profile itself provides an abundant information regarding the quality of products. Thus, forecasting temperature profile for each layer during additive manufacturing process is most feasible, by subsequently controlling the process parametric deviations, particularly with higher efficiency and faster response times. Melt pool temperature profile is dynamic and complex in nature. Thus, utilizing stand-alone traditional statistical or machine learning or deep learning models may not be effective. We have improved the forecasting performance by linearly combining CNN and LSTM networks to address the non-linearity from both spatial and sequential point of view. Time series analysis and forecasting is becoming an important research topic in recent years due to the availability of large amounts of data and high computational power. The present study demonstrated the application of CNN-LSTM model for layer-wise melt pool temperature forecasting during WAAM process. The melt pool temperature of the roof layer (layer 10) is forecasted by training the network with the previous layer's (from layer 1 to layer 9) temperature data. The performance of proposed CNN-LSTM model for all the experiments was evaluated using RMSE, MAE and MAPE. Further, results of proposed model were compared with the traditional benchmark time series models. The major conclusions drawn from this study are the following. The performance metrics of CNN-LSTM model for melt pool temperature forecasting followed a similar pattern for all the experiments, that shows the good repeatability of the proposed model. The comparative results with traditional models such as ETS, ARIMA, LR, SVM and RF have shown that the proposed model is capable of forecasting temperature with high accuracy. The RMSE value of the proposed model is decreased by 28.5%, 12%, 29.6%, 35.81%, 22.8% and 21.94% over MLP, CNN, GRU, LSTM, Bi-LSTM and Attention-LSTM models respectively. The right selection of hyper parameters of deep learning models is a major limitation for their general applicability. This usually follows a trial-and-error approach. In future work, inner structure of CNN-LSTM can be extensively studied for further improvement of the model's performance.

REFRENCES

[1] Wang, Chengcheng, et al. "Machine learning in additive manufacturing: State-of-the-art and perspectives." Additive Manufacturing 36 (2020): 101538.
[2] Zhu, Zuowei, et al. "Machine learning in tolerancing for additive manufacturing." CIRP Annals 67.1 (2018): 157-160.
[3] Shafaie, Majid, Maziar Khademi, Mohsen Sarparast, and Hongyan Zhang. "Modified GTN parameters calibration in additive manufacturing of Ti-6Al-4 V alloy: a hybrid ANN-PSO approach." The International Journal of Advanced Manufacturing Technology 123, no. 11 (2022): 4385-4398.
[4] Meng, Lingbin, et al. "Machine learning in additive manufacturing: a review." Jom 72.6 (2020): 2363-2377.
[5] Hart, Gus LW, et al. "Machine learning for alloys." Nature Reviews Materials 6.8 (2021): 730-755.
[6] Sarparast, Mohsen, Majid Ghoreishi, Tohid Jahangirpoor, and Vahid Tahmasbi. "Experimental and finite element investigation of high-speed bone drilling: evaluation of force and temperature." Journal of the Brazilian Society of Mechanical Sciences and Engineering 42, no. 6 (2020): 1-9.
[7] Li, Zhixiong, et al. "Prediction of surface roughness in extrusion-based additive manufacturing with machine learning." Robotics and Computer-Integrated Manufacturing 57 (2019): 488-495.
[8] Jin, Zeqing, et al. "Machine learning for advanced additive manufacturing." Matter 3.5 (2020): 1541-1556.
[9] Golmohammadi, Amir-Mohammad, Negar Jahanbakhsh Javid, Lily Poursoltan, and Hamid Esmaeeli. "Modeling and analyzing one vendor-multiple retailers VMI SC using Stackelberg game theory." Industrial Engineering and Management Systems 15, no. 4 (2016): 385-395.
[10] Fairley, Michael, David Scheinker, and Margaret L. Brandeau. "Improving the efficiency of the operating room environment with an optimization and machine learning model." Health care management science 22.4 (2019): 756-767.
[11] Sarparast, Mohsen, Majid Ghoreishi, Tohid Jahangirpoor, and Vahid Tahmasbi. "Modelling and optimisation of temperature and force behaviour in high-speed bone drilling." Biotechnology & Biotechnological Equipment 33, no. 1 (2019): 1616-1625.
[12] Baumann, Felix W., et al. "Trends of machine learning in additive manufacturing." International Journal of Rapid Manufacturing 7.4 (2018): 310-336.
[13] Gu, Grace X., et al. "Bioinspired hierarchical composite design using machine learning: simulation, additive manufacturing, and experiment." Materials Horizons 5.5 (2018): 939-945.
[14] Schelter, Sebastian, et al. "On challenges in machine learning model management." (2015).
[15] Bahrami, Javad, Mohammad Ebrahimabadi, Sofiane Takarabt, Jean-luc Danger, Sylvain Guilley, and Naghmeh Karimi. "On the Practicality of Relying on Simulations in Different Abstraction Levels for Pre-Silicon Side-Channel Analysis."
[16] Qi, Xinbo, et al. "Applying neural-network-based machine learning to additive manufacturing: current applications, challenges, and future perspectives." Engineering 5.4 (2019): 721-729.
[17] Johnson, N. S., et al. "Invited review: Machine learning for materials developments in metals additive manufacturing." Additive Manufacturing 36 (2020): 101641.
[18] Sadi, Mehdi, Yi He, Yanjing Li, Mahabubul Alam, Satwik Kundu, Swaroop Ghosh, Javad Bahrami, and Naghmeh Karimi. "Special Session: On the Reliability of Conventional and Quantum Neural Network Hardware." In 2022 IEEE 40th VLSI Test Symposium (VTS), pp. 1-12. IEEE, 2022.
[19] Qin, Jian, et al. "Research and application of machine learning for additive manufacturing." Additive Manufacturing (2022): 102691.
[20] Caggiano, Alessandra, et al. "Machine learning-based image processing for on-line defect recognition in additive manufacturing." CIRP annals 68.1 (2019): 451-454.
[21] Bahrami, Javad, Mohammad Ebrahimabadi, Jean-Luc Danger, Sylvain Guilley, and Naghmeh Karimi. "Leakage power analysis in different S-box masking protection schemes." In 2022 Design, Automation & Test in Europe Conference & Exhibition (DATE), pp. 1263-1268. IEEE, 2022.
[22] Yao, Xiling, Seung Ki Moon, and Guijun Bi. "A hybrid machine learning approach for additive manufacturing design feature recommendation." Rapid Prototyping Journal (2017).
[23] Bahrami, Javad, Viet B. Dang, Abubakr Abdulgadir, Khaled N. Khasawneh, Jens-Peter Kaps, and Kris Gaj. "Lightweight implementation of the lowmc block cipher protected against side-channel attacks." In Proceedings of the 4th ACM Workshop on Attacks and Solutions in Hardware Security, pp. 45-56. 2020.
[24] Sing, S. L., et al. "Perspectives of using machine learning in laser powder bed fusion for metal additive

manufacturing." Virtual and Physical Prototyping 16.3 (2021): 372-386.
[25] Ahmadinejad, Farzad, Javad Bahrami, Mohammd Bagher Menhaj, and Saeed Shiry Ghidary. "Autonomous Flight of Quadcopters in the Presence of Ground Effect." In 2018 4th Iranian Conference on Signal Processing and Intelligent Systems (ICSPIS), pp. 217-223. IEEE, 2018.
[26] Ko, Hyunwoong, et al. "Machine learning and knowledge graph based design rule construction for additive manufacturing." Additive Manufacturing 37 (2021): 101620.
[27] Hadiana, Hengameh, Amir Mohammad Golmohammadib, Hasan Hosseini Nasabc, and Negar Jahanbakhsh Javidd. "Time Parameter Estimation Using Statistical Distribution of Weibull to Improve Reliability." (2017).
[28] Chen, Po-Hsuan Cameron, Yun Liu, and Lily Peng. "How to develop machine learning models for healthcare." Nature materials 18.5 (2019): 410-414.
[29] Jiang, Jingchao, et al. "Achieving better connections between deposited lines in additive manufacturing via machine learning." Math. Biosci. Eng 17.4 (2020): 3382-3394.
[30] Zavareh, Bozorgasl, Hossein Foroozan, Meysam Gheisarnejad, and Mohammad-Hassan Khooban. "New trends on digital twin-based blockchain technology in zero-emission ship applications." Naval Engineers Journal 133, no. 3 (2021): 115-135.
[31] Li, Rui, Mingzhou Jin, and Vincent C. Paquit. "Geometrical defect detection for additive manufacturing with machine learning models." Materials & Design 206 (2021): 109726.
[32] Baturynska, Ivanna, Oleksandr Semeniuta, and Kristian Martinsen. "Optimization of process parameters for powder bed fusion additive manufacturing by combination of machine learning and finite element method: A conceptual framework." Procedia Cirp 67 (2018): 227-232.
[33] Meyer, Hanna, et al. "Improving performance of spatio-temporal machine learning models using forward feature selection and target-oriented validation." Environmental Modelling & Software 101 (2018): 1-9.
[34] Bozorgasl, Zavareh, and Mohammad J. Dehghani. "2-D DOA estimation in wireless location system via sparse representation." In 2014 4th International Conference on Computer and Knowledge Engineering (ICCKE), pp. 86-89. IEEE, 2014.
[35] Gobert, Christian, et al. "Application of supervised machine learning for defect detection during metallic powder bed fusion additive manufacturing using high resolution imaging." Additive Manufacturing 21 (2018): 517-528.
[36] Amini, Mahyar, Koosha Sharifani, and Ali Rahmani. "Machine Learning Model Towards Evaluating Data gathering methods in Manufacturing and Mechanical Engineering." International Journal of Applied Science and Engineering Research 15.4 (2023): 349-362.
[37] Paul, Arindam, et al. "A real-time iterative machine learning approach for temperature profile prediction in additive manufacturing processes." 2019 IEEE International Conference on Data Science and Advanced Analytics (DSAA). IEEE, 2019.
[38] Alfian, Ganjar, et al. "Improving efficiency of RFID-based traceability system for perishable food by utilizing IoT sensors and machine learning model." Food Control 110 (2020): 107016.
[39] Amini, Mahyar, and Aryati Bakri. "Cloud computing adoption by SMEs in the Malaysia: A multi-perspective framework based on DOI theory and TOE framework." Journal of Information Technology & Information Systems Research (JITISR) 9.2 (2015): 121-135.
[40] Mahmoud, Dalia, et al. "Applications of Machine Learning in Process Monitoring and Controls of L-PBF Additive Manufacturing: A Review." *Applied Sciences* 11.24 (2021): 11910.
[41] Amini, Mahyar. "The factors that influence on adoption of cloud computing for small and medium enterprises." (2014).
[42] Khanzadeh, Mojtaba, et al. "Quantifying geometric accuracy with unsupervised machine learning: Using self-organizing map on fused filament fabrication additive manufacturing parts." *Journal of Manufacturing Science and Engineering* 140.3 (2018).
[43] Akkiraju, Rama, et al. "Characterizing machine learning processes: A maturity framework." International Conference on Business Process Management. Springer, Cham, 2020.
[44] Amini, Mahyar, et al. "MAHAMGOSTAR.COM AS A CASE STUDY FOR ADOPTION OF LARAVEL FRAMEWORK AS THE BEST PROGRAMMING TOOLS FOR PHP BASED WEB DEVELOPMENT FOR SMALL AND MEDIUM ENTERPRISES." Journal of Innovation & Knowledge, ISSN (2021): 100-110.
[45] Liu, Rui, Sen Liu, and Xiaoli Zhang. "A physics-informed machine learning model for porosity analysis in laser powder bed fusion additive manufacturing." *The International Journal of Advanced Manufacturing Technology* 113.7 (2021): 1943-1958.
[46] Amini, Mahyar, et al. "Development of an instrument for assessing the impact of environmental context on adoption of cloud computing for small and medium enterprises." Australian Journal of Basic and Applied Sciences (AJBAS) 8.10 (2014): 129-135.
[47] Nojeem, Lolade, et al. "Machine Learning assisted response circles for additive manufacturing concerning metal dust bed fusion." International Journal of Management System and Applied Science 17.11 (2023): 491-501.
[48] Nickel, Maximilian, et al. "A review of relational machine learning for knowledge graphs." Proceedings of the IEEE 104.1 (2015): 11-33.
[49] Motalo, Kubura, et al. "evaluating artificial intelligence effects on additive manufacturing by machine

learning procedure." Journal of Basis Applied Science and Management System 13.6 (2023): 3196-3205.
[50] Fu, Yanzhou, et al. "Machine learning algorithms for defect detection in metal laser-based additive manufacturing: a review." *Journal of Manufacturing Processes* 75 (2022): 693-710.
[51] Amini, Mahyar, et al. "The role of top manager behaviours on adoption of cloud computing for small and medium enterprises." Australian Journal of Basic and Applied Sciences (AJBAS) 8.1 (2014): 490-498.
[52] Stathatos, Emmanuel, and George-Christopher Vosniakos. "Real-time simulation for long paths in laser-based additive manufacturing: a machine learning approach." *The International Journal of Advanced Manufacturing Technology* 104.5 (2019): 1967-1984.
[53] Amini, Mahyar, and Nazli Sadat Safavi. "Critical success factors for ERP implementation." International Journal of Information Technology & Information Systems 5.15 (2013): 1-23.
[54] Petrich, Jan, et al. "Multi-modal sensor fusion with machine learning for data-driven process monitoring for additive manufacturing." *Additive Manufacturing* 48 (2021): 102364.
[55] Amini, Mahyar, et al. "Agricultural development in IRAN base on cloud computing theory." International Journal of Engineering Research & Technology (IJERT) 2.6 (2013): 796-801.
[56] Snow, Zackary, et al. "Toward in-situ flaw detection in laser powder bed fusion additive manufacturing through layerwise imagery and machine learning." *Journal of Manufacturing Systems* 59 (2021): 12-26.
[57] Amini, Mahyar, et al. "Types of cloud computing (public and private) that transform the organization more effectively." International Journal of Engineering Research & Technology (IJERT) 2.5 (2013): 1263-1269.
[58] Akhil, V., et al. "Image data-based surface texture characterization and prediction using machine learning approaches for additive manufacturing." *Journal of Computing and Information Science in Engineering* 20.2 (2020): 021010.
[59] Amini, Mahyar, and Nazli Sadat Safavi. "Cloud Computing Transform the Way of IT Delivers Services to the Organizations." International Journal of Innovation & Management Science Research 1.61 (2013): 1-5.
[60] Douard, Amélina, et al. "An example of machine learning applied in additive manufacturing." *2018 IEEE International Conference on Industrial Engineering and Engineering Management (IEEM)*. IEEE, 2018.
[61] Amini, Mahyar, and Nazli Sadat Safavi. "A Dynamic SLA Aware Heuristic Solution For IaaS Cloud Placement Problem Without Migration." International Journal of Computer Science and Information Technologies 6.11 (2014): 25-30.
[62] Ding, Donghong, et al. "The first step towards intelligent wire arc additive manufacturing: An automatic bead modelling system using machine learning through industrial information integration." *Journal of Industrial Information Integration* 23 (2021): 100218.
[63] Amini, Mahyar, and Nazli Sadat Safavi. "A Dynamic SLA Aware Solution For IaaS Cloud Placement Problem Using Simulated Annealing." International Journal of Computer Science and Information Technologies 6.11 (2014): 52-57.
[64] Zhang, Wentai, et al. "Machine learning enabled powder spreading process map for metal additive manufacturing (AM)." *2017 International Solid Freeform Fabrication Symposium*. University of Texas at Austin, 2017.
[65] Sharifani, Koosha and Amini, Mahyar and Akbari, Yaser and Aghajanzadeh Godarzi, Javad. "Operating Machine Learning across Natural Language Processing Techniques for Improvement of Fabricated News Model." International Journal of Science and Information System Research 12.9 (2022): 20-44.
[66] Du, Y., T. Mukherjee, and T. DebRoy. "Physics-informed machine learning and mechanistic modeling of additive manufacturing to reduce defects." *Applied Materials Today* 24 (2021): 101123.
[67] Sadat Safavi, Nazli, et al. "An effective model for evaluating organizational risk and cost in ERP implementation by SME." IOSR Journal of Business and Management (IOSR-JBM) 10.6 (2013): 70-75.
[68] Chen, Lequn, et al. "Rapid surface defect identification for additive manufacturing with in-situ point cloud processing and machine learning." *Virtual and Physical Prototyping* 16.1 (2021): 50-67.
[69] Sadat Safavi, Nazli, Nor Hidayati Zakaria, and Mahyar Amini. "The risk analysis of system selection and business process re-engineering towards the success of enterprise resource planning project for small and medium enterprise." World Applied Sciences Journal (WASJ) 31.9 (2014): 1669-1676.
[70] Yaseer, Ahmed, and Heping Chen. "Machine learning based layer roughness modeling in robotic additive manufacturing." *Journal of Manufacturing Processes* 70 (2021): 543-552.
[71] Sadat Safavi, Nazli, Mahyar Amini, and Seyyed AmirAli Javadinia. "The determinant of adoption of enterprise resource planning for small and medium enterprises in Iran." International Journal of Advanced Research in IT and Engineering (IJARIE) 3.1 (2014): 1-8.
[72] Chen, Lequn, et al. "Rapid surface defect identification for additive manufacturing with in-situ point cloud processing and machine learning." Virtual and Physical Prototyping 16.1 (2021): 50-67.
[73] Safavi, Nazli Sadat, et al. "An effective model for evaluating organizational risk and cost in ERP implementation by SME." IOSR Journal of Business and Management (IOSR-JBM) 10.6 (2013): 61-66.
[74] Guo, Shenghan, et al. "Machine learning for metal additive manufacturing: Towards a physics-informed data-driven paradigm." Journal of Manufacturing Systems 62 (2022): 145-163.
[75] Khoshraftar, Alireza, et al. "Improving The CRM System In Healthcare Organization." International Journal of Computer Engineering & Sciences (IJCES) 1.2 (2011): 28-35.
[76] Ren, K., et al. "Thermal field prediction for laser scanning paths in laser aided additive manufacturing by physics-based machine learning." Computer Methods in Applied Mechanics and Engineering 362 (2020): 112734.

[77] Abdollahzadegan, A., Che Hussin, A. R., Moshfegh Gohary, M., & Amini, M. (2013). The organizational critical success factors for adopting cloud computing in SMEs. Journal of Information Systems Research and Innovation (JISRI), 4(1), 67-74.
[78] Zhu, Qiming, Zeliang Liu, and Jinhui Yan. "Machine learning for metal additive manufacturing: predicting temperature and melt pool fluid dynamics using physics-informed neural networks." Computational Mechanics 67.2 (2021): 619-635.
[79] Amini, Mahyar and Ali Rahmani. "Agricultural databases evaluation with machine learning procedure." Australian Journal of Engineering and Applied Science 8.6 (2023): 39-50.
[80] Zhang, Lu, et al. "From machine learning to deep learning: progress in machine intelligence for rational drug discovery." Drug discovery today 22.11 (2017): 1680-1685.
[81] Jackson, Keypi, et al. "Increasing substantial productivity in additive manufacturing procedures by expending machine learning method." International Journal of Mechanical Engineering and Science Study 10.8 (2023): 363-372.
[82] Opuiyo, Atora, et al. "Evaluating additive manufacturing procedure which was using artificial intelligence." International Journal of Science and Information System 13.5 (2023): 107-116.
[83] Amini, Mahyar, and Ali Rahmani. "Machine learning process evaluating damage classification of composites." Journal 9.12 (2023): 240-250.
[84] Yun, Chidi, et al. "Machine learning attitude towards temperature report forecast in additive manufacturing procedures." International Journal of Basis Applied Science and Study 9.12 (2023): 287-297.
[85] Shun, Miki, et al. "Incorporated design aimed at additive manufacturing through machine learning." International Journal of Information System and Innovation Adoption 16.10 (2023): 823-831.