MODELING THE TRACK WIDTH OF INCONEL ALLOY IN LDED USING ARTIFICIAL NEURAL NETWORK

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Laser-directed energy deposition (LDED) is a kind of additive manufacturing. It is hard to understand the deposition process during the yielding of track width of Inconel alloy, and many trials are required to obtain the ideal LDED settings. In this situation, numerical simulations are helpful since they can forecast trends without requiring extensive testing. Artificial neural networks can develop a precise prediction model with the help of weight values of the trained network. In this research paper, Inconel 718 alloy is deposited using LDED process by varying three input parameters which are laser power (P), powder feed rate (PFR), and deposition speed (V). The track width of single-track profile of deposited material is modeled using an artificial neural network. The model's prediction strength is found to be almost equal to actual values, with a difference of less than 5%. The statistical errors for quality characteristics are less than 5%, and the regression values for training, testing, and validation data are greater than 95%, indicating excellent prediction strength. The average percentage error and mean square error of the developed network were found less than 5%.

Keywords: Laser-directed energy; additive manufacturing; Inconel alloy; artificial neural network.

1. Introduction

Directed Energy Deposition (DED) stands as a pivotal and advanced technology within the realm of additive manufacturing, distinguished by its capability to not only facilitate the precise repair of fractured or worn metal components but also to enable the application of protective or functional coatings onto a diverse array of substrates, thereby enhancing material properties and extending the lifespan of critical engineering structures [1]. Its growing popularity in the industry can be attributed to its ability to significantly minimize material waste and control the rising costs associated with precious metal items. This process involves the utilization of a high-power laser, which meticulously scans the surface of the substrate plate, simultaneously melting the deposited powder

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and creating a molten pool, thereby facilitating the precise fabrication and repair of metal components with minimal resource expenditure [2]. During the process stage, the metal, provided in the form of either wire or powder, is meticulously supplied and integrated, serving as the foundational material that undergoes transformation under precise conditions to achieve the desired structural outcomes [3]. Consequently, this technique proves instrumental in restoring defective metal parts to their original condition, thereby mitigating the need for component disposal. With this objective in focus, the methodology has been rigorously evaluated not only on flat surfaces but also under challenging deposition conditions, such as the repair of fractured edges and other complex geometries [4]. The DED process has great potential for large-scale production of automotive and aerospace components [5]. However, several challenges remain, including the need to reduce reliance on the experimental trial-and-error approach to optimize processing parameters [6]. Experimental optimization is money and time-consuming because of the numerous operational factors. The LDED-AM process is also quite sensitive to disruptions [7]. A small change in the process variables (such as the processing speed, laser absorptivity, and initial temperature) may result in significant variations in dilution (the percentage of the surface layer made up of melted substrate) and in the transient heating/cooling rate and the overall shape of the melt pool. These variations may harm the deposited clad layer, which in turn affects the physical and mechanical properties, and process stability of the fabricated part [8]. To solve these problems, other approaches like artificial neural networks are needed.

To determine the best process parameters setting, it is required many trials for each application while limiting the number of passes, which has an impact on the cost and overall time. Through numerical models, the number of trials may be decreased. For instance, a model may be used to forecast the ideal overlap ratio. It would take numerous experiments to do it experimentally.

The recently developed mathematical models' Multi-layer Multi-Bead (MLMB), which are based on geometrical functions, exhibit high performance together with simplicity. As reported by Froend et al. [7] highlights that it improves surface quality for optimal bead geometry, eliminating the need for complex FEM software. The MLMB models predict individual bead profiles based on overlapping layers through modeling and investigations. Ocelik et al. [9] developed a recursive model to represent the situation, successfully implementing the algorithm in bead formation. However, the model has flaws, notably assuming equal material deposition for all beads. In reality, varying amounts of powder reach the target, leading to beads with differing cross-sectional areas due to the inefficiency of the powder collection system [10]. Maurya et al. [11] optimized the track height considering the process parameters such as powder feed rate, laser power, and scan speed found the optimized track height, and validated it with the experimental results. To forecast the single-track dimension and the steady-state melt pool temperature, Li et al. [12] created a multivariable analytical model. Additionally, a feedback system used to control the temperature, and the height of the melt pool was accomplished using the created model. Based on the energy balances and process mass, Kaplan and Groboth [13] created an analytical process model to predict the clad shape geometry and substrate temperature. They point out that the powder flux distribution affects the laser energy distribution and process powder catchment. Merve et al. [14] deposited the single tracks sectioned and performed the experimental work, further developing a numerical model to validate the results obtained by experiments. Using regression analysis, mathematical formulas were developed to predict several features of the single-clad track (height, breadth, and depth). The effect of process factors on the geometrical properties of the single-clad track was thoroughly investigated using analysis of variance (ANOVA). Yuze et al. [15] designed a thorough analytical model that takes into account both the geographical distribution of heated powder and the attenuated laser power intensity for the catchment efficiency and single-track dimension prediction. Botez et al. [16] investigated the distinct types of defects into the thermally deposited layer using contact and non-contact types of inspection techniques which were microhardness and ultrasound, respectively. Rontescu et al. [17] synthesized the titanium alloy using direct melting laser sintering to investigate the mechanical properties of this alloy. Becherescu et al. [18] analysed the characteristics of two different material deposition techniques which were pulased laser deposition and high-power impulse magnetron sputtering. Costache et al. [19] used the selective laser sintering technique for powder deposition and investigated the mechanical and chemical properties of of deposited material.

To understand the mechanism of input and output process parameters of laser directed energy deposition method for a work material; an accurate and reliable prediction model is required. Therefore, it is attempted to develop an artificial intelligence-based prediction model for LDED construct track profile, which was rarely found in the literature review. The goal of this research paper is to build and verify a reliable artificial neural network model that may be able to predict the LDED construct single track profile of Inconel alloy.

2. Experimental procedures

In the current investigation, an indigenously built LDED system available at RRCAT Indore, India, was utilized. The system uses an ytterbium-doped fiber laser (λ=1070 nm) that can operate in continuous-wave mode at 2 kW laser power.

Optical systems and collimator lenses help the fiber laser to target the spot precisely. For powder feed management, a screw-type volumetric feeder was used. Argon served as both a shielding and a transport gas. The powder delivery system, gas feeder system, and laser system connected to the deposition head, which was installed on an overhead gantry system. The substrate plate was supported by a fixed workstation during the deposition procedure. Fig. 1 depicts the different aspects of equipment utilized for single-track LDED deposition.

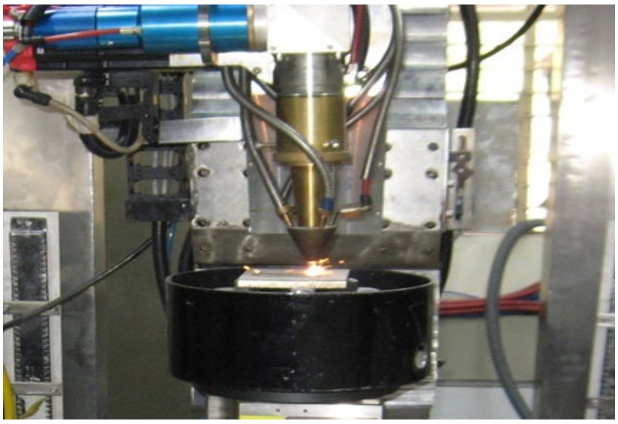
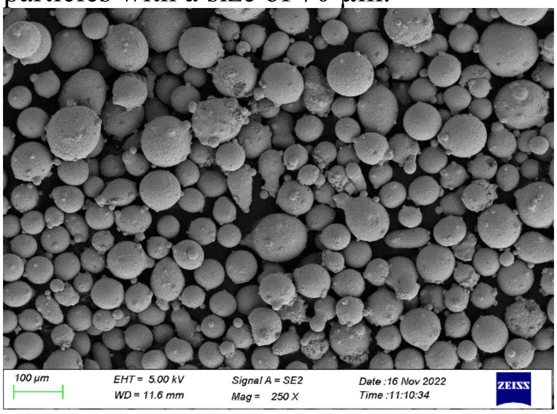
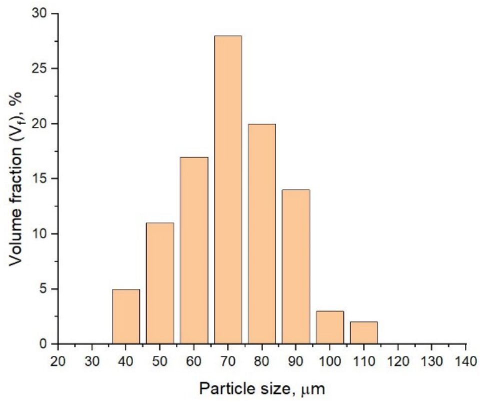


Fig. 1. L-DED system used for experimental work

For the deposition of single tracks, a gas-atomized powder of Alloy 718 with a nominal chemical composition as standard was used (see Table 1). Fig. 2 (a) depicts an SEM picture of powder particles. According to Fig. 2 (b), the powder's particle size distribution was found between 40 µm to 110 µm, with a mean particle size of 70 µm. Fig. 2 (b) also depicts the particle volume fraction concerning particle size, with the majority of the volume fraction being seen for particles with a size of 70 µm.



(a)



(b)

Fig. 2. (a) SEM micrograph of powder particles of Inconel 718, (b) Volume fraction of different particle size

Table 1

Composition of IN718 powder in % by weight [17]

Element		**Ni**	**Cr**	**Nb**	**Mo**	**Ti**	**Al**	**Co**	**Cu**	**C**	**Fe**
Weight (%)	**Min**	50	17	4.755	2.8	0.65	0.200	≤1	≤0.3	≤0.08	Balance
	Max	55	21	.5	3.3	1.15	.80				

While most process variables remained fixed, several variables, including laser power (P), powder feed rate (PFR), and deposition speed (V) were adjusted at three distinct levels. Table 2 contains a list of significant process parameters that were obtained through early experimental rounds and employed in the current investigation.

Table 2

Process parameters used for preliminary iterations

Process Parameters	**Related Value**
Deposition speed (m/min)	0.4, 0.6 and 0.8
Laser power (W)	800, 1000 and 1200
Feed rate (g/min)	6, 9 and 12
Laser spot diameter (Ds) (mm)	2
Laser stand-off distance (mm)	20

Table 3 depicts the whole experimental design data. Tracks of 30 mm in length were placed on top of a substrate plate that measured 100 x 100 x 10 mm^3. The parameter sets associated with 27 single tracks were deposited as seen in Fig. 3. To conduct additional experimental research, the tracks were cut using wire EDM perpendicular to the direction of deposition.

(a) (b)

Fig. 3. Photographs of (a) single track deposition and (b) Microscopy image of deposition

Table 3

Track width corresponds to design factors.

Track No.	**P (W)**	**V (m/min)**	**F (g/min)**	**Track Width (mm)**
1	800	0.4	6	1.936
2	800	0.4	9	2.081

3	800	0.4	12	2.188
4	800	0.6	6	1.852
5	800	0.6	9	1.931
6	800	0.6	12	2.013
7	800	0.8	6	1.784
8	800	0.8	9	1.802
9	800	0.8	12	1.817
10	1000	0.4	6	2.258
11	1000	0.4	9	2.328
12	1000	0.4	12	2.403
13	1000	0.6	6	1.912
14	1000	0.6	9	2.054
15	1000	0.6	12	2.128
16	1000	0.8	6	1.832
17	1000	0.8	9	1.914
18	1000	0.8	12	2.012
19	1200	0.4	6	2.426
20	1200	0.4	9	2.534
21	1200	0.4	12	2.612
22	1200	0.6	6	2.322
23	1200	0.6	9	2.458
24	1200	0.6	12	2.533
25	1200	0.8	6	2.012
26	1200	0.8	9	2.336
27	1200	0.8	12	2.422

3. Artificial Neural Network Modeling

To enhance the capability of the LDED process, secure liaison between input and output parameters of this process is essential. Artificial neural network (ANN) is a promising modeling technique that consists of three important layers which are input, hidden and output [20,21]. In the present study, ANN tool of MATLAB® software is used to develop feed forward back propagation-based ANN architecture for track width. To predict the output parameter i.e. track width value from the neural network model it initially requires training. In this study, Levenberg-Marquardt algorithm is used to train the neural network model. And momentum based gradient decent method converges the learning of network whereas performance of the network is evaluated using mean square error. Fitness of data into neural network is performed using regression analysis as shown in Fig.4. Regression correlation coefficient (R) values for training data, testing data, and validation data are found as 0.99397, 0.99199 and 0.9981, respectively as exposed by Fig. 4. These correlation coefficient values are closer to one that confirms the prediction strength of the developed model. Fig. 4 consists of four regression plots comparing the target values to the output values for different phases of a neural network model: training, validation, testing, and overall performance. Each plot also includes a fit line and the R-value, indicating the correlation between the output and the target. In the top left of Fig. 4; training plot shows the linear relationship between the output and the target values. The regression values (R = 0.99397) of training data indicates a very high correlation between the output and the target. Likewise strong trends between output and target data are found for validation (R =0.99199) and test date (R = 0.9981). Therefore, the overall model reveals compelling performance between the output and the target. The high R-values in all plots indicate that the neural network model has performed exceptionally well in predicting the target values across training, validation, and testing phases. Slight deviations in the fit line slopes and intercepts indicate minor differences in model performance across different data sets, but overall, the model has a strong predictive capability. Table 4 shows the comparative values between ANN predicted and experimental values. The errors between actual experimental and predicted values were found almost equal and less than 5%. It shows the strength of the developed model is adequate for the prediction of track width.

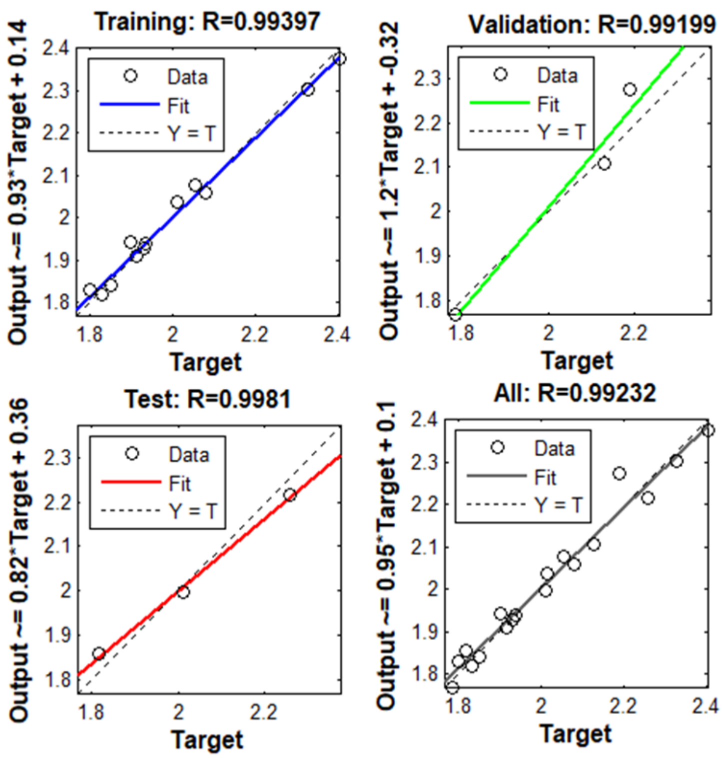


Fig. 4. Regression plots for track width

Fig. 5 compares the actual and predicted values of Track Width (TW) over number of tests. The x-axis is labelled with number of testing values and ranges from 1 to 9, indicating the sequence of test values while the y-axis is labelled with Track Width (TW) values (mm) and ranges from 1.9 to 2.4 mm that indicating the measurements of track width. In Fig. 5 predicted values follow the trend of actual experimental values of TW hence the developed model is reliable and accurate.

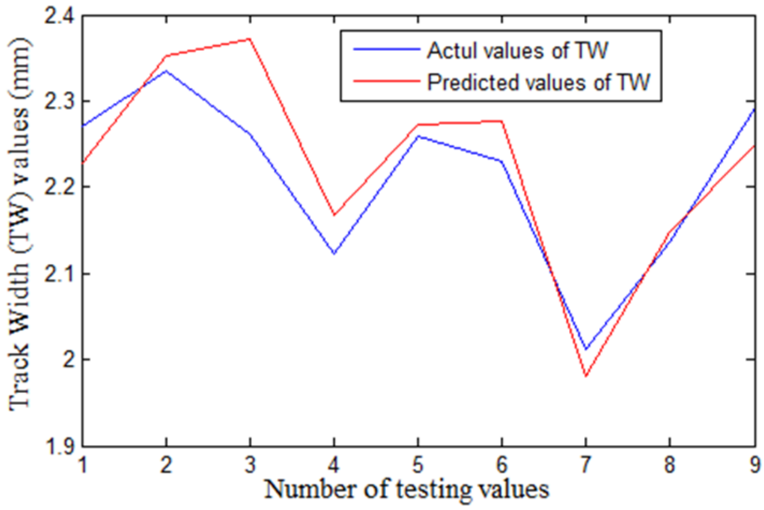


Fig. 5. Comparison between actual and predicted values of track width.

Table 4

Values of artificial neural network model for track width

Values	Track Width (mm)
Average experimental values of testing	1.9275
Average prediction values	1.8358
Mean absolute percentage error (%)	4.77
Mean squared error	0.302
Mean absolute deviation	0.091
Root mean square error	0.54
Average percentage prediction error (%)	4.98

3. Conclusion

Experiments are conducted to measure the track width of Inconel alloy using laser directed energy deposition method at RRCAT Indore, (India). Three design factors, viz. power, feed rate, and speed are elected for the experimentation. Experiments are designed using an L27 orthogonal array and then measure the track width. Artificial neural network technique is used to develop the prediction model for the track width of Inconel alloy. The statistical errors for quality characteristics are less than 5%, and the regression values for training, testing, and validation data are greater than 95%, indicating excellent prediction strength. The average percentage error and mean square error of the developed model are less than 5%. Hence, it shows that the developed model prediction strength is accurate and reliable.

Future research direction, perspectives, limitations: This study has successfully developed a robust artificial neural network (ANN) model for predicting the track width of Inconel alloy in laser-directed energy deposition (LDED) process. Expanding the model to predict the track width for other emerging materials can validate its versatility and applicability across different metals.

Further optimization of the process parameters, including but not limited to laser power, powder feed rate, and deposition speed, can lead to improved quality and consistency of the deposited tracks. Other artificial intelligence-based modeling methods can also be used for the present work.

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