

CHAPTER

6

PHYSICS CONSTRAINED NEURAL NETWORKS FOR THERMAL PREDICTION IN LASER DEPOSITION

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6.1 INTRODUCTION

The Laser Direct Energy Deposition (LDED) process is a popular technique capable of producing complex metallic parts (Kladovasilakis et al., 2021). The cooling rate of the melt pool is one of the primary factors affecting the microstructure. The energy density delivered through the laser determines the energy distribution in the bulk and surface of the print and thus the cooling rate. Hence, the thermal history during the LDED process is very complex (Xia et al., 2020), with heat losses through powder ejecta, reflection losses from the melt pool and baseplate, mechanical properties of the baseplate, conduction, and advection of heat dependent on the melt pool fluid motion. From the perspective of additive manufacturing, the low density, high strength, and superior biocompatibility of Ti-6Al-4V alloy have led to various powder bed fusion manufacturing methods developed for this alloy in the past 20 years (Nouri et al., 2021), and a large number of

works on the effects of processing parameters on the microstructure or properties of Ti-6Al-4V samples have been studied. Due to the rapid solidification associated with the LDED process, the as-deposited materials often contain a high proportion of α martensite phase, which significantly reduces the mechanical properties and thermal behavior of LDED components.

The optimization of deep neural network (DNN) to accurately predict the thermal history during LDED of Ti-6Al-4V, seeks to unlock insights into the precise thermal distribution and heat transfer patterns as the laser interacts with the Ti-6Al-4V substrate. These comprehensive predictions enable engineers and researchers to comprehensively analyze thermal behavior, assess potential problems, and devise targeted strategies to enhance the overall process. The process of optimizing the DNN involves meticulous calibration and fine-tuning of numerous network parameters, such as layer architecture, activation functions, learning rates, and regularization techniques (Raiaan et al., 2024). Additionally, this optimization effort entails acquiring an extensive dataset of thermal histories obtained from multiphysics model simulations (Cai et al., 2021).

The rich dataset serves as the foundation for training and validating the DNN, enabling it to learn the complex relationships between process parameters and thermal responses. The optimization of the DNN showcases the intricate and dynamic nature of this research field. By pushing the boundaries of multiphysics modeling and NN, it promises to revolutionize the understanding and control of the LDED process, opening up a multitude of possibilities for enhancing the efficiency and quality of Ti-6Al-4V printed parts.

6.2 BASICS OF DEEP NEURAL NETWORKS

In a DNN, the input data is subjected to nonlinear transformations by the hidden layers in the middle of the input and output layers, as shown in Figure 6.1. This allows for the gradual extraction of relatively high features and representations. The network can learn more intricate

characteristics and relationships within the input data as the number of hidden layers grows, resulting in improved accuracy and generalization (Feng et al., 2019).

These models can represent the complex interactions between process parameters, material qualities, and thermal behavior, leading to accurate predictions that can be made in real-time (Wang et al., 2022).

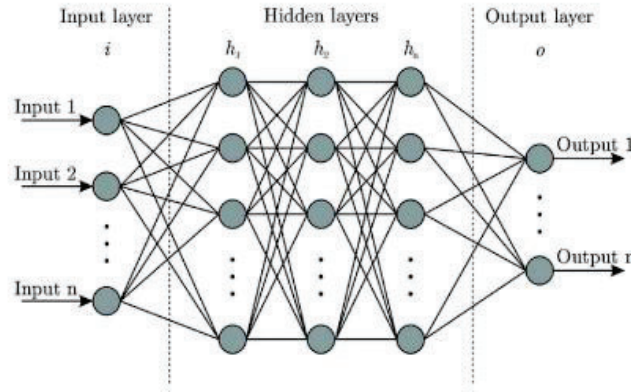


Figure 6. 1 An example of deep neural network architecture
(Source: Bre et al., 2018)

Techniques from the field of DNN can recognize patterns and derive hypotheses from massive datasets. Successive layers of connected neurons process the incoming data. Each layer is responsible for a distinct function, such as extracting features or classifying data. During training, adjustments are made to the weight of the links between the neurons to maximize the effectiveness of the DNN. A typical node of a DNN will have the following three primary components, as shown:

$$y_i = \varphi \left(\sum w_{ij} \theta_j + b_i \right) \quad (6.1)$$