Prediction of Printing Performance of Additively Manufactured M2052 Alloy by Simulation Coupled with Machine Learning

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Abstract: M2052 alloy is a twinned damping alloy with damping and shape memory effects. This paper employs a simulation-machine learning-experimentation approach to establish a connection between the different dampings and mechanical properties of M2052 alloy produced under various printing process parameters. Utilizing the Single Bead Parametric Simulation and Microstructure Simulation modules in ANSYS simulation software, datasets of melt pool morphology and microstructure were generated. Five machine learning models are selected and ultimately optimized to establish the relationship between process parameters and microstructure. The use of machine learning effectively predicts the performance of specimens under different process parameters.

Keywords: M2052； damping alloy；simulation; machine learning.

1 Introduction

MnCu alloy is a typical twin-shaped damping alloy, and its excellent damping performance mainly comes from the high migration rate of {101} twin boundaries caused by the martensitic phase transformation, accompanied by low critical twin/de-twinning stress and tetragonal lattice distortion (1-c/a). Due to its outstanding damping and mechanical properties, it has a wide range of applications in fields such as radio frequency communication, sensors and actuators, energy harvesters, and biomedical devices. The development of the Mn-20Cu-5Ni-2Fe (at. % M2052) alloy is relatively mature. It is characterized by its ability to simultaneously achieve excellent mechanical and damping properties, and has a broad potential for application in complex service conditions such as deep space and deep sea. Typically, M2052 alloy is manufactured using traditional methods such as vacuum induction melting, forging, and rolling techniques to produce finished components. However, in recent years, the precision requirements for MnCu alloy components have been increasing, along with demands for complex spatial gyration structures and even lattice structures. Traditional processing methods are unable to fully meet the economic and time cost requirements for these types of applications, to a certain extent restricting the prospects for the use of MnCu alloys.

Selective laser melting (SLM) is a typical additive manufacturing process capable of integrally forming complex spatial structures while maintaining extremely high heat input (10^{5-7} W/cm^3), a large temperature gradient in the molten pool (10^6 K/m), and a high cooling rate (10^{3-8} K/s). The rapid heating and cooling characteristics of the thermal source, along with the thermal cycling effect of layer-by-layer melting and printing, facilitate the formation of fine and dispersed equiaxed crystals as well as dense and tough complex components. The properties of SLM can also effectively assist in the forming of MnCu alloy components, increase the solubility limit, refine the grain structure, and promote the formation of metastable phases. Therefore, M2052 high-damping alloy prepared using SLM technology holds broad research and application prospects.

2 Experimental procedure

Materials and equipment

Preparation of M2052 alloy powder with a particle size of 15-53 μm using electrode induction melting atomization method. The powder composition is listed in Table 1. The morphology and size of M2052 powder are shown in Figure 1.

Table 1 Chemical composition of the M2052 power.

Elements	Mn	Cu	Ni	Fe	O
wt. %	Bal.	21.66	4.69	1.65	0.11

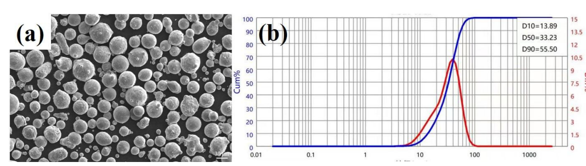

Fig. 1 (a)SEM morphology of M2052 powders (b) particle size distribution of alloy powder

The specimens were fabricated using a Pro X200 laser powder bed fusion (LPBF) system. The standard for setting the printing process parameters was based on the laser volumetric energy density (Ev), which is determined by the following factors: laser power (P), scan speed (v), hatch spacing (h), and powder layer thickness (t). The volumetric energy density can be calculated using the formula(1):

$$E_v = P/(v \times h \times t) \quad (1)$$

Simulation calculation and machine learning prediction algorithms

By designing simulated experimental data effectively, rich training and testing sets can be provided for machine learning models, thereby improving the prediction accuracy and generalization ability of the models. In this study, the machine learning algorithm's training and testing data were mainly obtained using the Single Bead Parametric Simulation and Microstructure Simulation modules within the finite element simulation and cellular automata.

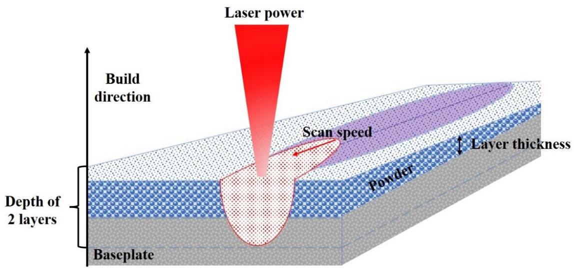

Fig.2 Schematic diagram of SLM process

3 Result and discussion

Machine learning based prediction of molten pool morphology

For the as-printed M2052 alloy, the damping performance originates from the relaxation effect of twin grain boundaries, as well as the energy dissipation caused by the fcc→fct phase transformation and the paramagnetic→ferromagnetic transition-induced lattice distortion. According to Cochardt's magnetomechanical damping model, under the same strain amplitude, the damping capacity and the saturation magnetostriction constant (λ) of the twinned damping alloy exhibit a positive correlation, and the value of λ can be established as a functional relationship with the degree of tetragonal lattice distortion.

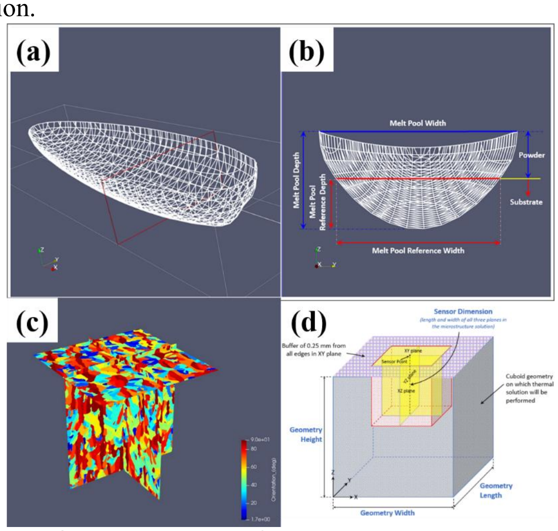

Fig.3 (a) (b) Schematic diagram of molten pool simulation, (c) (d)

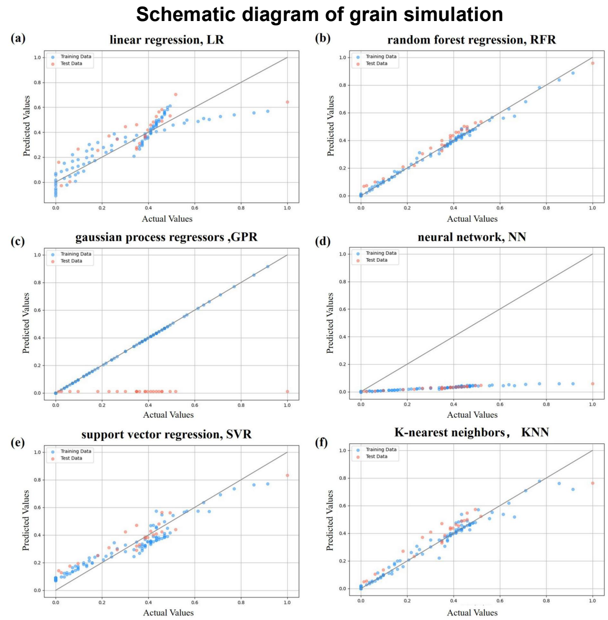

Fig.4 The depth fitting effect of different machine learning models on the melt pool (a)LR (b)RFR (c)GPR (d)NN (e)SVR (f)KNN

4 Conclusion

The experimental results of this study demonstrate that Random Forest Regression (RFR) and Support Vector Regression (SVR) exhibit desirable generalization capabilities and predictive accuracy when dealing with small sample learning processes. Based on the simulation calculation results and machine learning model predictions, the relationship between process parameters and performance is ultimately established. The model developed in this work can effectively predict the mechanical and damping performance of printed samples under different printing parameters.

5 Acknowledgments

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