Collaborative Optimization of High Strength, Ductility,and Low Porosity for Selective Laser Melting GH4169 Superalloy by Fusion of Data-Driven and Theory

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Abstract: Multi-performance collaborative optimization is a trend for improving the properties of additive manufacturing products and expanding their applications. A fusion of data-driven and theory approach is proposed for multi-performance objective optimization of selective laser melting. Firstly, a global, stepwise, centrally dense hexagonal design of experiments is applied to the additive manufacturing of 65 GH4169 nickel superalloy materials each employing different laser processing conditions. Secondly, 4 multiple stepwise regression models are established to quantify the complex relationship between laser process parameters and relative density, yield strength, tensile strength, and elongation. Thirdly, a stepwise regression non-dominated sorting genetic algorithm with relative density energy criterion constraints is developed to achieve multi-performance objective process parameters collaborative optimization. Finally, a high strength, ductility, and low porosity component is manufactured by this approach. Compared to traditional optimization approaches, this approach can more accurately and efficiently achieve multiple process parameters collaborative recommendations.

Keywords: Additive manufacturing (AM), Selective laser melting (SLM), Fusion of data-driven and theory (FDDT), GH4169 superalloy, Multi-performance objective, Process parameters collaborative optimization

1 Introduction

Additive manufacturing (AM) is one of the fundamental technologies for rapidly moving towards intelligent manufacturing. Selective laser melting (SLM), as a typical metal AM technology, has dozens of parameters[1-2] as well as complex heat and mass transfer phenomena in molten pools [3] which lead to collaborative optimization being extremely difficult[4].

In the paper, a fusion of data-driven and theory approach is proposed for multi-performance objective optimization of selective laser melting GH4169 superalloy. 4 key process parameters, laser power(P), scanning speed(v), hatch space(h), and layer thickness(t), were tuned by the intelligent recommendation systems and the locally conflicting properties, relative density, yield strength, tensile strength, and elongation were optimized.

2 Experimental Procedure

Bone shape GH4169 samples (FIGURE 6FIGURE 6) were fabricated by SLM with a global, stepwise, centrally dense hexagonal design (Table 1).

Table 1 Design of Experiments

No.	*P* (W)	*v* (mm/s)	*h* (μm)	*d* (μm)
Group1				
1	260	700	90	20
2	290	900	100	20
3	320	1100	110	20
4	350	1300	120	20
Group2				
1	100	300	60	20
2	150	600	75	30
3	200	900	90	40
4	250	1200	105	50
5	300	1500	120	60
6	350	1800	135	70
7	400	2100	150	80

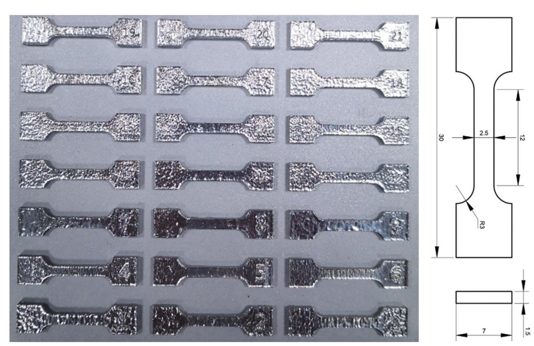


Figure 6 SLM samples with engineering drawing

3 Result and discussion

3.1 Model construction and evaluating

The four properties prediction models for relative density, tensile strength, yield strength, and tensile strain were constructed by stepwise regression modelling (Figure 7). The process parameters recommendation system assembly the prediction model and multi-objective optimization algorithm Non-dominated Sorting Genetic Algorithm (NSGA-Ⅱ) (Figure 8, Figure 9, Figure 10).

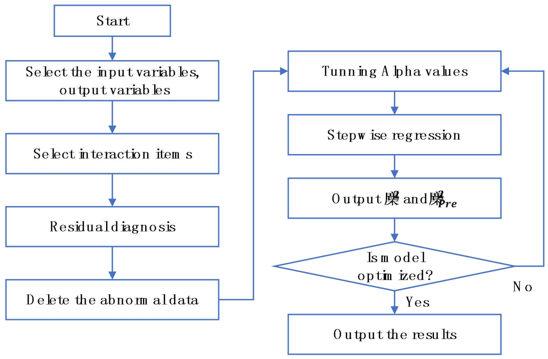


Figure 7 Stepwise regression model construction procedure

The evaluating metrics of predictive models, $RSME$, R^2, $R^2{}_{adj}$, $R^2{}_{pre}$, are the following formula:

$$RSME = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}\text{ , i=1, 2, …, } n \tag{1}$$

$$R^2 = 1 - \frac{\sum(y_i - \hat{y})^2}{\sum(y_i - \bar{y})^2} \tag{2}$$

$$R^2{}_{adj} = 1 - \left\{\frac{\sum(y_i - \hat{y})^2}{\sum(y_i - \bar{y})^2}\right\}\left(\frac{n-1}{n-p-1}\right) \tag{3}$$

$$R^2{}_{pre} = 1 - \frac{\sum_1^n \left(\frac{e_i}{1-h_i}\right)^2}{\sum_1^n (y_i - \bar{y})^2} \tag{4}$$

3.2 COLLABORATIVE OPTIMIZATION

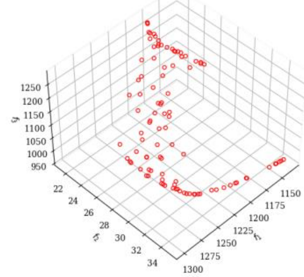
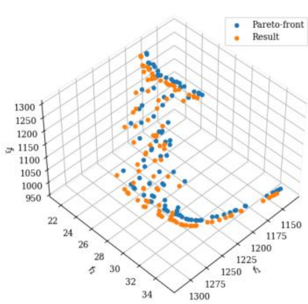


Figure 8 The Pareto front of 3



properties

Figure 9 The recommendation points with 3 properties

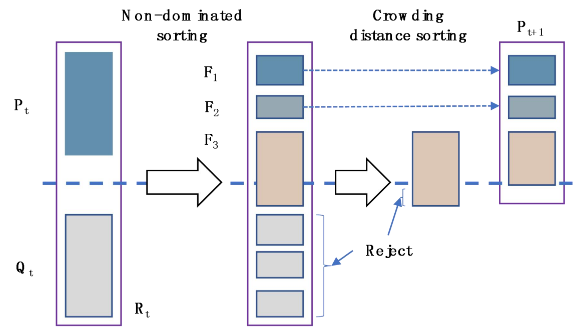


Figure 10 NSGA-Ⅱ algorithm procedure illustration

Conclusions

(1) 4 key properties predictive models were established by stepwise regression model.

(2) 4 key properties were collaboratively optimized as well as process parameters intelligently recommended by NSGA-Ⅱalgorithm.

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