

Research and Density Prediction of Laser-Wire-Directed Energy Deposition Additive Manufacturing Process Based on 304 Stainless Steel

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Abstract

The internal porosity generated during laser-wire-directed energy deposition (LW-DED) additive manufacturing of 304 stainless steel significantly impacts the mechanical properties, corrosion resistance, and long-term reliability of the product. Investigating the influence of processing parameter combinations on component density and establishing a density prediction model is an effective way to improve manufacturing quality. This paper systematically explores the influence of laser power, scanning speed, wire feed speed, and shielding gas pressure on component density. Based on this, four density prediction models including Support Vector Regression (SVR), CatBoost, K-Nearest Neighbors (KNN), and Gaussian Process Regression (GPR) are constructed. Analysis results show that the SVR model has the best predictive performance, with a training set determination coefficient of 0.9356. The maximum mean absolute error (MAE) and root mean square error (RMSE) on the test set are 0.137 and 0.175, respectively. Experimental results show that the average error between the model's predicted density and the experimentally measured value is only 0.184%. The above research provides support for optimizing process parameters in laser-fed directional energy deposition additive manufacturing of 304 stainless steel.

1 Introduction

Laser wire-directed energy deposition (LW-DED) uses a laser as a heat source to simultaneously melt and deposit metal wires layer by layer to form three-dimensional components. It has outstanding advantages such as high forming efficiency, high material utilization, and the ability to achieve integrated forming of complex components and high-performance repair^[1]. Using this technology to prepare complex stainless steel components can effectively overcome the bottlenecks of traditional subtractive manufacturing, such as serious material waste, high processing difficulty and long manufacturing cycle when preparing complex structures. It can also make the product components maintain the characteristics of good mechanical properties, corrosion resistance and low cost of 304 stainless steel. It has broad application prospects in aerospace, biomedicine and marine engineering^[2–4]. However, like AM technologies such as powder bed melting, LW-DED technology is also prone to pores during component preparation, which affect the compactness and mechanical properties of the components, and thus restrict its application in key load-bearing structures with extremely high requirements for fatigue performance and reliability^[5–8]. Therefore, how to effectively suppress pore defects has become a key issue for LW DED stainless steel.

To address the porosity defects that are prone to occur during additive manufacturing, the main solutions currently include process parameter and path optimization^[9–11], substrate or material preheating^[12–14], and hot isostatic pressing post-processing^[15, 16]. Among these, process parameter optimization is the source control method for achieving high density components. It does not require additional equipment or complex post-processing and can directly suppress the formation of internal porosity defects by controlling energy input and molten pool state, making it the core foundation for preparing high-density components. Currently, a large number of studies have been exploring the process optimization of LW-DED technology. On the one hand, researchers have used multiphysics coupled numerical simulation techniques such as discrete element method (DEM)^[17, 18] and computational fluid dynamics (CFD)^[19, 20] to clarify the dynamic evolution of the molten pool, the distribution of the melt temperature field, and the evolution of pores during the manufacturing process. From the perspective of multiphysics, this has revealed the intrinsic mechanism of pore nucleation, growth, and merging, providing theoretical support and fundamental guidance for defect control and process parameter optimization. On the other hand, single-factor experiments can reveal the influence of a single process parameter

on the density of components. Based on this, a density prediction model can be constructed by combining machine learning algorithms, which can quantitatively characterize the complex nonlinear relationship between process parameters and component density, achieve accurate prediction of component density, significantly reduce experimental costs, and realize rapid screening and intelligent optimization of process windows^[21–23]. Other studies have pointed out that, with the help of synchrotron radiation X-ray in-situ imaging and other means^[24–28], the morphology of the molten pool and internal defects during the manufacturing process have been monitored in real time. The relationship between key process parameters such as laser power and scanning speed and porosity characteristics has been directly established, providing experimental basis and control foundation for real-time identification and closed-loop control of porosity defects.

The aforementioned process optimization strategies provide important references for reducing component porosity. However, the specificity of material properties is the core variable determining the forming quality of components, directly affecting energy absorption, molten pool behavior, and microstructure evolution during the forming process, ultimately leading to significant forming differences. Therefore, simply relying on generalized process parameters is insufficient to meet the manufacturing needs of diverse materials, and subsequent process optimization research needs to be conducted in conjunction with specific material characteristics. Current research on LW-DED technology mainly focuses on materials such as titanium alloys, nickel-based superalloys, and aluminum alloys. For titanium alloys, researchers focus on optimizing key process parameters such as laser power and scanning speed to precisely control the heat input during the forming process, which can effectively suppress component oxidation and crack defects, thereby achieving microstructure refinement and mechanical property improvement^[29–31]. In the forming of nickel-based superalloy components, existing research mainly focuses on process parameter matching and crack suppression mechanisms, alleviating problems such as easy cracking and uneven microstructure distribution by optimizing the scanning path and improving the shielding gas^[32, 33]. Aluminum alloys are highly sensitive to hydrogen, and forming defects are mainly spherical hydrogen pores. Adding silicon (Si) can reduce the diffusion coefficient of hydrogen in the molten pool and decrease the hydrogen enrichment area before solidification, thereby effectively suppressing hydrogen pores. Researchers have also been able to promote the closure of surface pores and form a dense, defect-free surface layer by adding Si and optimizing laser power^[34–36]. However, systematic research on the processing of stainless steel components, especially those made from wire, is still insufficient, and there are still gaps in the research on related process mechanisms and pore control.

Stainless steel components fabricated using LW-DED technology can be used in micro-cooling channels, steam turbine blades, and precision aero-engine turbine blades^[2, 37, 38]. Currently, research on stainless steel fabrication using LW-DED technology mainly focuses on exploring the mechanical properties, corrosion resistance, and microstructure of the components, with no reports on the correlation between the process and porosity^[39–41]. Meanwhile, existing research on the correlation between the process and porosity of additive manufacturing stainless steel is mainly conducted in processes such as powder bed melting and laser powder delivery directional energy deposition, but different processes have fundamental differences in thermal cycling, molten pool dynamics, and solidification behavior^[42–44]. Therefore, directly applying the research conclusions based on other additive manufacturing processes has significant limitations. It is crucial to conduct targeted and in-depth research to systematically reveal the complex interactive influence mechanism of multiple process parameters in LW-DED technology on the density of stainless steel.

This study investigated the influence mechanism of laser power, scanning speed, wire feed speed, and gas pressure on relative density using single-factor experiment, and established a correlation dataset between these four parameters and relative density. Based on this, orthogonal experiments were designed to explore the interaction effects of these four parameters on relative density. Finally, Support Vector Regression (SVR), CatBoost, K-Nearest Neighbors (KNN), and Gaussian Process Regression (GPR) were applied to construct relative density prediction models, and comparative analyses were performed. The results show that the models can not only effectively predict relative density under different combinations of process parameters, but also intuitively reveal the interaction relationship between each process parameter and relative density, providing important technical support for process optimization and quality control of 304 stainless steel.

2 Experimental Methods

2.1 Materials and Experimental Apparatus

The laser wire feeding directional energy deposition system used in this study mainly consists of a fiber laser with a wavelength of 1070 nm, an automatic wire feeder, and a three-axis moving platform. The experimental apparatus is shown in Fig. 1. The 304 stainless steel welding wire is inclined at a 45° angle to the horizontal plane and fed into the center of the molten pool using a feedforward method^[45]. Argon gas with a purity of 99.99% is backblown through a gas nozzle with an inclination angle of 45° to suppress high-temperature oxidation. A 100 mm × 50 mm × 5 mm 304 stainless steel substrate and a 0.8 mm diameter 304 stainless steel wire were prepared for the experiment. The substrate was sanded with sandpaper and wiped with alcohol before deposition to remove surface stains. The chemical composition of the stainless steel used for the wire is shown in Table 1.

Table 1 Chemical composition of 304 stainless steel welding wire (wt%)									
Element	C	Si	Mn	P	S	Cr	Ni	Cu	N
Wire	0.046	0.44	1.04	0.028	0.04	18.06	8.05	0.03	0.048

2.2 Sample Preparation

LW-DED technology involves many process parameters, but laser power, scanning speed, and wire feed speed directly dominate energy input, material deposition rate, and molten pool thermodynamic behavior. These are the most sensitive variables determining key defects such as incomplete fusion and porosity. Their interaction forms key process indicators such as linear energy density and cladding rate, which are crucial for predicting and controlling density. Meanwhile, gas pressure is a key environmental parameter controlling the protective effect and cooling rate, and has a decisive impact on oxidation inhibition and defect control. Therefore, this study selected four parameters—laser power, scanning speed, wire feed speed, and gas pressure—for experiments. To investigate the influence of these four parameters on sample density, 52 parameter combinations were designed using a univariate method. Four samples were prepared under each parameter combination. The ranges of the process parameters are as follows: laser power 500–1400 W, scanning speed 450–1000 mm/min, wire feed speed 80–200 cm/min, and gas pressure 0.05–0.4 MPa. The remaining process parameters are fixed as follows: spot diameter is 2 mm, wire feed angle is 45°, and wire feed direction is forward, as shown in Table 2.

Table 2
DED Process Parameters

Parameters	Ranges	Steps
Laser power(W)	500–1400	50
Scanning speed(mm/min)	450–1000	50
Wire feed speed(cm/min)	80–200	10
Gas pressure(Mpa)	0.05–0.4	0.05
Spot diameter(mm)	2	—
Wire feeding angle(°)	45	—
Wire feeding direction	Front	—

2.3 Relative Density Measurement Methods

Relative density measurement methods include optical microscopy, X-ray computed tomography, and Archimedes' method^[46]. Here, Archimedes' method is used to measure the density of the prepared sample. The apparatus is shown in Fig. 2(a). The electronic balance is LC-JA3003. The mass of each sample in air and in water are measured respectively. The sample density is calculated by Eq. (1) ^[47]

1

In the formula, ρ_w is the water density, ρ_a is the air density, and the sample density is the combined density of the weld and the substrate, as shown in Fig. 2(b). To obtain the weld density, this study calculates the volume ratio of the weld and the substrate in the sample, and then derives the actual density of the weld. The specific steps are as follows: First, the sample cross-section is polished with 400-grit, 800-grit, and 1500-grit sandpaper, polished to a mirror finish with 50 nm silica suspension, and etched in a mixed acid solution (hydrofluoric acid: nitric acid: water = 1:2:50) for 60 seconds. Second, the cross-sectional morphology is observed with a microscope, and the cross-sectional area of the weld is measured using ImageJ software. Then, the arithmetic mean of the cross-sectional areas of the weld at both ends of the sample is taken as the cross-sectional area of the weld, and the arithmetic mean of the cross-sectional areas of the sample at both ends measured by a micrometer is taken as the sample cross-sectional area. The weld quality and weld density are calculated using formulas (2) and (3)

2

3

Where m_s is the sample mass, m_{ss} is the substrate mass, L is the sample length, ρ_{ss} is the density of the 304 stainless steel substrate, and V_w is the weld volume. Finally, the relative density is obtained from Eq. (3)

3

When using the Archimedes method for density measurement, errors may occur due to factors such as moisture retention in the sample affecting density, uneven surface tension affecting buoyancy, and volume measurement. To minimize these errors, the sample is dried before each measurement.

3 Results and Discussion

3.1 Single-Factor Experiment

To systematically investigate the independent effects of laser power, scanning speed, wire feed speed, and shielding gas pressure on weld density, a single-factor experimental scheme was designed using the above four parameters as variables. The relevant experimental results and analysis are as follows.

3.1.1 Laser Power

Under the conditions of a fixed scanning speed of 600 mm/min, wire feed speed of 130 cm/min, and shielding gas pressure of 0.3 MPa, the influence of laser power variation within the range of 500–1400 W on weld density is shown in Fig. 3(a). When the laser power is below 650 W, insufficient laser energy input makes it difficult to form a stable keyhole effect, resulting in insufficient metal vapor back pressure and a shallow molten pool depth, thus easily leading to porosity and incomplete fusion defects. Simultaneously, the molten pool cools rapidly at low power, which not only causes a sharp decrease in gas solubility in the molten pool and the precipitation of a large amount of supersaturated gas to form pores, but also inhibits the feeding effect of liquid metal, thereby inducing shrinkage defects. As the laser power increases, the density gradually increases, reaching a maximum of 99.76% when the laser power reaches 800 W. When the laser power gradually increases from 800 W to 1400 W, the keyhole inside the molten pool experiences an excessively large aspect ratio due to the excessive input energy. Under the dynamic imbalance of surface tension and steam back pressure, the keyhole wall violently oscillates and collapses locally, forming large keyhole pores.

3.1.2 Scanning Speed

The scanning speed variation range was selected as 450–1000 mm/min, and the laser power, wire feed speed and shielding gas pressure were fixed at 800 W, 600 mm/min, and 0.3 MPa, respectively. The effect of shielding gas pressure variation on density is shown in Fig. 3(b). When the scanning speed is less than 550 mm/min, the laser energy input is too high, accelerating the flow of liquid metal inside the molten pool and enhancing internal convection disturbance. Strong convection causes liquid metal at the edge of the molten pool to splash, and the resulting voids cannot be fully filled during subsequent solidification, thus forming irregular pore defects. As the scanning speed increases, the density gradually increases, reaching a maximum of 99.70% when the scanning speed reaches 600 mm/min. When the scanning speed exceeds 700 mm/min, the density decreases rapidly for two reasons: Firstly, the excessively high scanning speed shortens the interaction time between the laser and the wire and substrate, and some wire may only melt on the surface, or even remain in a solid or semi-solid state before being deposited on the substrate. Gaps exist between these incompletely melted wires and the substrate, leading to a sharp decrease in density. On the other hand, the cooling rate during the solidification stage of the molten pool increases as the heat input decreases. The solidification rate of the molten pool is faster than the escape rate of the bubbles. Some bubbles are wrapped by the rapidly solidified molten metal film, eventually forming spherical pores in the cladding layer.

3.1.3 Wire Feed Speed

The wire feed speed was selected as the range of 80–200 cm/min, and the laser power, scanning speed, and shielding gas pressure were fixed at 800 W, 600 mm/min, and 0.3 MPa, respectively. The effect of wire feed speed variation on density is shown in Fig. 3(c). When the wire feed speed is less than 140 cm/min, the density is

less than 99%. Too low a wire feed speed results in less metal entering the molten pool per unit time, a lower droplet transition frequency, and uneven droplet size, making it impossible to form a continuous and stable cladding layer. In some areas, insufficient wire supply leads to filling gaps, which form pores after solidification. When the wire feed speed is increased to 160 cm/min, the density reaches 99.81%. As the wire feed speed continues to increase, the density decreases slightly. When the wire feed speed is excessively high, there is a surge in the volume of filler wire entering the molten pool per unit time. This excess of material overwhelms the available laser energy input, meaning that the power delivered to the pool becomes insufficient to fully melt all the incoming wire. As a result, some wire segments are not completely melted before they are forcibly pushed deeper into the pool by the continuous arrival of subsequent wires. These incompletely melted, still solid or semi-solid wires then create direct mechanical impacts against the bottom region of the molten pool. Such impacts seriously disrupt the dynamic stability and smooth flow pattern of the molten pool, leading to violent perturbations and the ejection of molten metal in the form of spatter. The combined effect of this material loss through spatter and the instability-induced defects ultimately results in a significant decrease in weld density.

3.1.4 Shielding Gas Pressure

The shielding gas pressure variation range was selected as 0.05–0.4 MPa, and the laser power, scanning speed, and wire feed speed were fixed at 800 W, 600 mm/min, and 160 cm/min, respectively. The effect of shielding gas pressure variation on density is shown in Fig. 3(d). When the gas pressure is below 0.2 MPa, the gas flow rate is insufficient, making it difficult to effectively disperse the plasma generated by the interaction between the laser and the material and substrate. The plasma accumulates above the molten pool and forms a dense plasma cloud. This cloud weakens the absorption of the laser by the material through refraction and scattering, and insufficient energy input leads to incomplete fusion defects. When the gas pressure increases to 0.2 MPa, the plasma cloud above the molten pool is effectively dispersed, the absorption of laser energy by the material is enhanced, and the density gradually increases, eventually reaching 99.85%. As the shielding gas pressure continues to rise, the weld density gradually decreases. When the gas pressure is too high, the resulting high-speed gas flow strongly impacts the surface of the molten pool. This intense impact not only disturbs the surface of the molten pool, causing it to entrain surrounding air and thus introduce bubbles and potential porosity, but also significantly accelerates the solidification rate of the molten pool by enhancing convective cooling. Under the combined effect of these two factors, the weld density ultimately decreases significantly.

3.2 Orthogonal Experiment

To systematically investigate the coupled effects of laser power, scanning speed, wire feed speed, and gas pressure on weld density, a series of single-factor experiments were first conducted to identify the preliminary influence trends and suitable parameter ranges of each factor. On this basis, an orthogonal experiment was then designed to evaluate the interactive effects among the four process parameters. The specific combinations of process parameters used in the orthogonal experiment are presented in Table 3. The experimental results indicate that when the laser power is set to 800 W, the scanning speed to 600 mm/min, the wire feed speed to 160 cm/min, and the gas pressure to 0.2 MPa, the weld density reaches its maximum value of 99.84%. This optimum result is essentially consistent with the findings obtained from the preceding single-factor experiments, confirming the reliability of the observed parameter combination.

To quantify and test the main effects and interactions of multiple factors on the research indicators, the study performed both variance analysis (ANOVA) and range analysis on the orthogonal experimental data. The range

analysis was used to rank the influence strength of each factor, while the variance analysis further evaluated the statistical significance of these effects. The results of the variance analysis are presented in Table 4. Within the single-factor variance analysis, the sum of squares of the deviations for laser power is relatively larger than that of the other factors, indicating that laser power exerts a significant influence on weld density compared to the other process parameters. However, the sums of squares of the deviations for travel speed, wire feed speed, and gas pressure are much smaller than the error term, resulting in their F-ratios being much smaller than the critical value, indicating that these three factors have no significant effect on weld density under the experimental conditions. The range analysis results are shown in Table 5. The effect of laser power on density shows a trend of first increasing and then decreasing. Among the five experimental levels, level 2 corresponds to a peak density of 99.244%. Subsequently, as the power continues to increase, the density drops sharply, reaching only 96.114% at level 5, indicating a clear optimal power window; excessively high power leads to a significant decrease in density. Meanwhile, the ranges for scanning speed and wire feed speed are 0.378% and 0.22%, respectively, indicating that these two parameters have relatively low influence on density within the current parameter range. Notably, the range for gas pressure shows a slow increasing trend, with density gradually rising from 98.04% at level 1 to 98.272% at level 5. This indicates that appropriately increasing the shielding gas flow rate is beneficial for improving molten pool protection and reducing porosity formation, but its impact is limited. Comprehensive analysis of the orthogonal experimental data including both range and variance results clearly shows that laser power is the dominant variable controlling weld density. In contrast, individual adjustments of the other parameters within the experimental range have relatively limited impact on density. Their effects are substantially smaller than that of laser power. Consequently, process optimization aimed at improving weld density should prioritize the precise control of laser power.

Table 3
Orthogonal experimental process parameters and relative density

No.	Laser power(W)	Scanning speed(mm/min)	Wire feed speed(cm/min)	Gas pressure(MPa)	Relative density
1	600	400	100	0.1	98.779
2	600	600	120	0.2	99.133
3	600	700	140	0.3	98.931
4	600	900	160	0.4	98.800
5	600	800	180	0.5	98.900
6	800	400	120	0.3	99.079
7	800	600	140	0.4	99.215
8	800	600	160	0.2	99.845
9	800	900	180	0.1	98.833
10	800	800	100	0.2	99.248
11	900	400	140	0.5	98.560
12	900	600	160	0.1	98.869
13	900	700	180	0.2	99.027
14	900	900	100	0.3	98.805
15	900	800	120	0.4	98.761
16	1000	400	160	0.2	97.617
17	1000	600	180	0.3	97.745
18	1000	700	100	0.4	97.940
19	1000	900	120	0.5	97.392
20	1000	800	140	0.1	97.672
21	1200	400	180	0.4	96.259
22	1200	600	100	0.5	96.374
23	1200	700	120	0.1	96.054
24	1200	900	140	0.2	95.771
25	1200	800	160	0.3	96.124

Table 4
ANOVA results.

Factors	Sum of squares	Degrees of freedom	F-ratio	F critical value
Laser power(W)	32.6	4	3.908	3.01
Scanning speed(mm/min)	0.469	4	0.056	3.01
Wire feed speed(cm/min)	0.151	4	0.018	3.01
Gas pressure(MPa)	0.144	4	0.017	3.01
Error	33.36	16	—	—

Table 5
Range analysis results.

Factors	Mean 1	Mean 2	Mean 3	Mean 4	Mean 5	Range
Laser power(W)	98.908	99.244	98.806	97.734	96.114	3.13
Scanning speed(mm/min)	98.06	98.269	98.358	97.98	98.14	0.378
Wire feed speed(cm/min)	98.23	98.143	98.03	98.25	98.154	0.22
Gas pressure(MPa)	98.04	98.161	98.138	98.196	98.272	0.232

3.3 Relative Density Prediction Model

To achieve accurate prediction of sample density under different combinations of process parameters, this section introduces machine learning methods and establishes a density prediction model based on existing experimental data.

3.3.1 Comparison Of Different Models

The dataset was randomly divided into training and test sets in an 8:2 ratio using random sampling to ensure consistent sample distribution. Based on this, an integrated pipeline consisting of normalization processing and machine learning algorithms was constructed. A 5-fold cross-validation strategy was employed for grid search to perform global optimization on the training set, ultimately determining the optimal combination of model parameters suitable for density prediction. Four machine learning algorithms including Support Vector Machine Regression (SVR), CatBoost, Gaussian Process Regression (GPR), and K-Nearest Neighbors (KNN) were selected to construct density prediction models. The best modeling method was selected by comparing and analyzing the predictive performance of each model. To evaluate the predictive performance of different models, three indicators were used: coefficient of determination (R^2), mean absolute error (MAE), and root mean square error (RMSE). For a given set of n experimental parameters

4
5
6

In the formula, y_i represents the i -th true value, $\bar{y}$ represents the mean of the true values, and $\hat{y}_i$ represents the i -th predicted value. The results are shown in Fig. 4. The SVR model performs best overall among the four models,

while the KNN model performs worst. The SVR model has an R^2 of 0.900 on the test set, a MAE of only 0.137, and an RMSE of 0.175. The training and test sets are highly consistent, demonstrating good generalization and no overfitting. The RMSE(/)MAE ratio of 1.277 indicates a stable prediction error distribution without abnormally large errors. The KNN model performs the worst among all compared models, with a test set R^2 of 0.844, MAE of 0.208, and RMSE of 0.243. Although its training set R^2 reaches 0.921, the significant drop on the test set suggests insufficient generalization. Figure 5 shows the prediction-observation plots of the four models (SVR, KNN, GPR, CatBoost), all exhibiting good overall fitting. Among them, SVR performs best, with all points within the confidence and prediction bands, and its prediction stability is significantly better than the others.

3.3.2 Model Validation

With the wire feed speed fixed at 160 cm/min and the air pressure fixed at 0.2 MPa, four models were used to predict the sample relative density when the laser power ranged from 500 to 1400 W and the scanning speed ranged from 300 to 1000 mm/min. Contour plots were then generated, as shown in Fig. 6. The results show that the SVR model yielded the best predictions. When the laser power was fixed, the sample relative density initially increased and then decreased with increasing scanning speed, consistent with previous single-factor experiments. The relative density reached its highest point at a laser power of 739 W and a scanning speed of 571 mm/min, indicating consistency between the model predictions and experimental results. Notably, the CatBoost model's predictions exhibited a gridded pattern. This is because the CatBoost model is an ensemble model based on decision trees, where each tree generates a rectangular region through feature threshold segmentation. The KNN model's predictions showed poor continuity, as the prediction surface of the KNN model algorithm is essentially based on the Voronoi diagram of the training sample distribution. The boundaries of these Voronoi units are the perpendicular bisectors of the lines connecting the sample points, forming irregular polygons. Therefore, the SVR model is more suitable for predicting sample relative density.

To verify the reliability of the SVR model, this paper explores the interaction between laser power and wire feed speed, as well as between laser power and gas pressure. The results are shown in Fig. 7. Figure 7(a) shows the sample relative density obtained by adjusting the laser power and wire feed speed under the conditions of a scanning speed of 600 mm/min and a gas pressure of 0.2 MPa. When the laser power is fixed, the sample relative density first increases and then decreases with the increase of the wire feed speed. The relative density reaches a maximum of 99.52% when the laser power is 776 W and the wire feed speed is 148 cm/min. Figure 7(b) shows the sample relative density obtained by adjusting the laser power and gas pressure under the conditions of a scanning speed of 600 mm/min and a wire feed speed of 160 cm/min. When the laser power is fixed, the sample relative density increases with increasing gas pressure until it reaches its maximum value at approximately 0.15 MPa. With further increases in gas pressure, the relative density decreases. The relative density reaches a maximum of 99.68% when the laser power is 738 W and the gas pressure is 0.15 MPa. The interaction between process parameters and relative density shown in Fig. 6 is largely consistent with the conclusions of previous single-factor and orthogonal experiments, demonstrating the reliability of the SVR model.

Based on the above analysis, this study selected six representative data points from Figs. 6(a) and 7 to conduct additional validation experiments, thereby further verifying the model's reliability. The corresponding experimental data are presented in Table 6. A detailed analysis of the prediction results reveals that the deviations between the predicted values and the measured values are small across all six experimental groups. This finding not only confirms the high reliability of the model but also demonstrates its good prediction accuracy. It is worth noting

that when the density is low, the deviation between the model prediction and the experimental measurement is greater. This phenomenon may be caused by the following three reasons: First, high-porosity samples inherently contain more open pores on their surfaces, which leads to a rougher surface quality compared to dense samples. When the Archimedes method is employed for density measurement, such rough and porous surfaces are more prone to the adhesion of microbubbles during immersion. These attached bubbles introduce additional buoyancy, thereby reducing the accuracy of the density measurement. Second, the process parameter combinations that result in high porosity are often located near the boundaries of the experimental parameter space. Operating in these boundary regions tends to cause poor melt pool stability, making the process more sensitive to random fluctuations or external disturbances. As a result, the reproducibility of the measured density values in high-porosity regimes is generally lower. Third, because experimental designs are usually concentrated in regions with good density, data in high-porosity regions are sparse, and the model lacks sufficient training samples, resulting in insufficient extrapolation ability.

Table 6 Experimental verification data							
NO.	Laser power(W)	Scanning speed(mm/min)	Wire feed speed(cm/min)	Shielding gas pressure(MPa)	Predicted value	Measured value	AE
1	720	757	160	0.2	98.690	98.763	0.073
2	1363	400	160	0.2	96.664	96.346	0.318
3	850	600	124	0.2	99.421	99.491	0.070
4	1106	600	158	0.2	97.593	97.726	0.333
5	904	600	160	0.15	99.046	98.999	0.047
6	1253	600	160	0.45	96.568	96.832	0.264

4 Conclusions

The study focuses on 304 stainless steel and investigates the coupling effect of process parameters on density during laser wire feed additive manufacturing. Based on the influence of process parameters on density, various machine learning methods were used to construct predictive models between process parameters and density, revealing a complex nonlinear relationship between them. The following conclusions were obtained:

- (1) Laser power, scanning speed, wire feed speed, and gas pressure affect density by regulating energy input, molten pool dynamics stability, and plasma. The relationship between these process parameters and density generally exhibits a non-monotonic change pattern of first increasing and then decreasing.
- (2) Laser power is the dominant variable controlling density and plays a decisive role in energy input. Individual adjustments to scanning speed, wire feed speed, and gas pressure within the experimentally set range have little impact on density. This indicates that density is most sensitive to changes in laser power, and process optimization should prioritize precise control of laser power.
- (3) Evaluation revealed that the SVR model was the most accurate in predicting porosity among the four models, with an R^2 of 0.936 on the training set and 0.900 on the test set. The RMSE to MAE ratio was 1.277, indicating excellent generalization ability and high stability of the prediction model. Simultaneously, the contour plots

visually presented the interaction between process parameters and porosity, providing important support for the process optimization of 304 stainless steel.

In summary, this study, through systematic experiments and cross-validation modeling, elucidated the synergistic mechanism of multiple process parameters on porosity formation in the DED process of 304 stainless steel. The established process window optimization criteria and SVR quantitative model can provide reliable theoretical basis and process guidance for the practical engineering application of high-quality, low-defect additive manufacturing of 304 stainless steel.

Declarations

Conflicts of Interest:

The authors declare no conflict of interest.

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Author Contribution:

Conceptualization, Y.M.; Methodology, Y.M.; Software, Y.M.; Validation, Y.M.; Formal analysis, Y.M.; Investigation, Y.M. and X.Z.; Data curation, Y.M. and X.Z.; Writing—original draft, Y.M.; Writing—review & editing Y.M., Supervision, H.Y.; Project administration, Y.M. All authors have read and agreed to the published version of the manuscript.

Data Availability Statement:

The original contributions presented in this study are included in the article. Further inquiries can be directed to the corresponding author.

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Figures

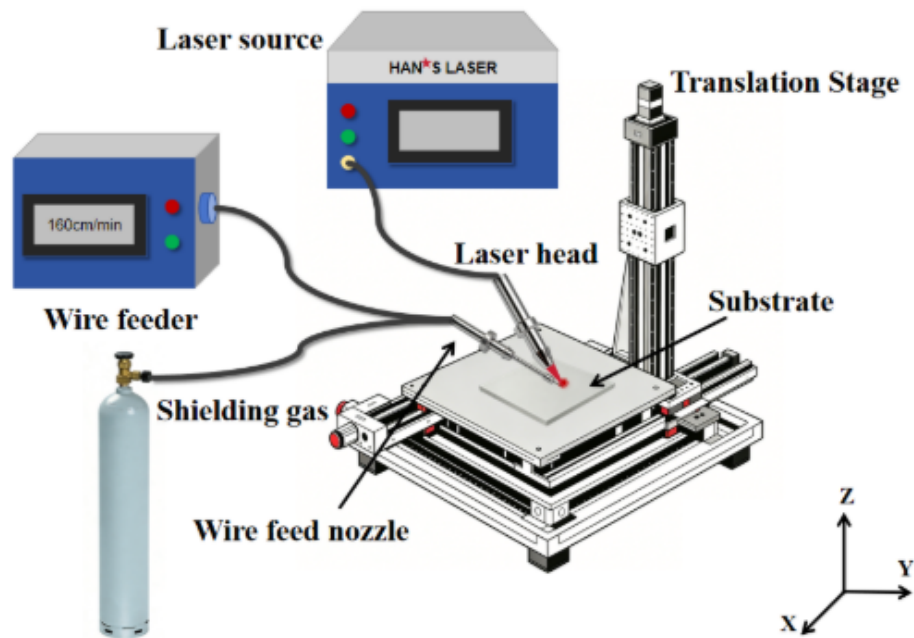


Figure 1
Instrument configuration for laser-guided directional energy deposition.

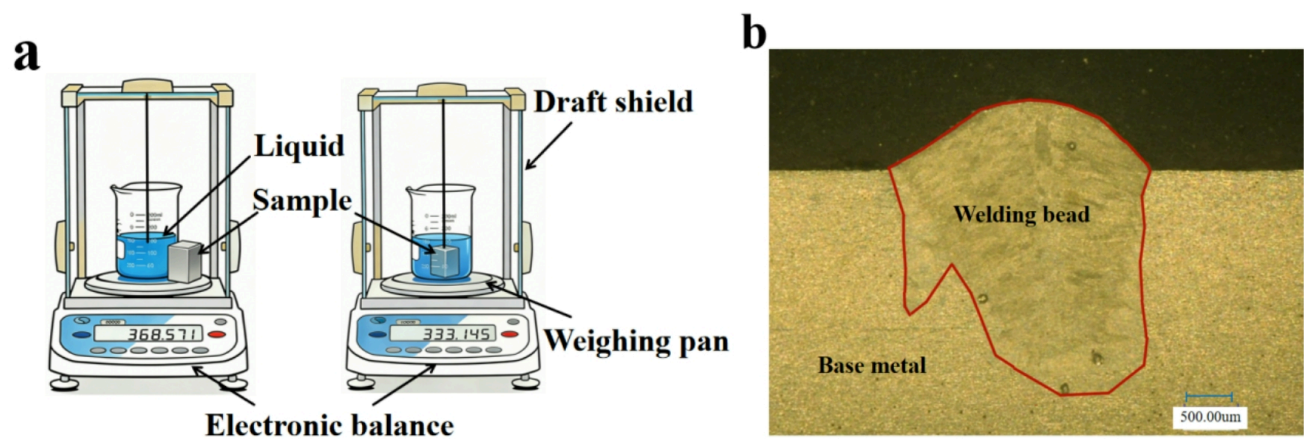


Figure 2

Detailed description of relative density measurement in the LW-DED process. a. Density measuring device. b. Schematic diagram of weld cross-section.

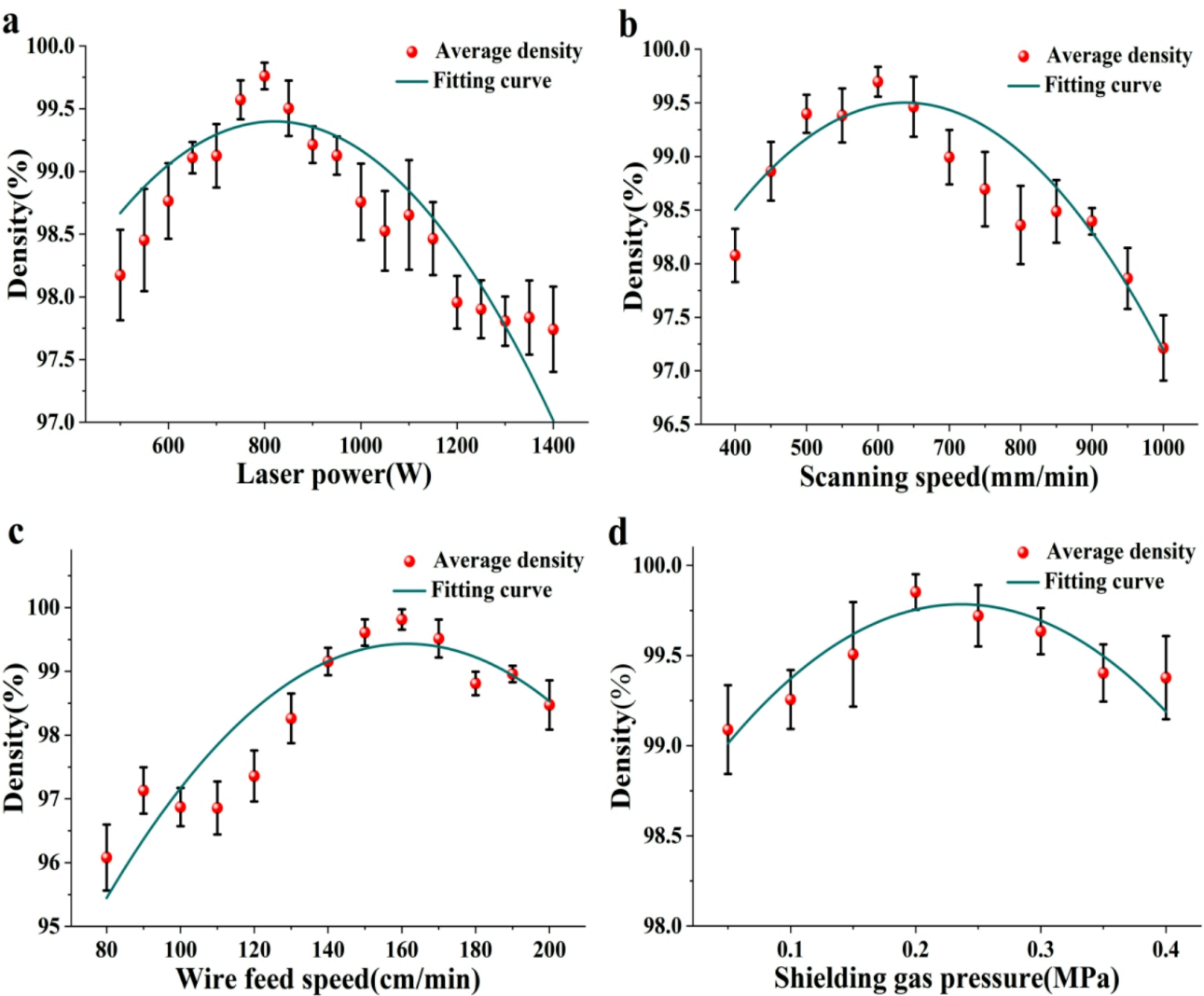


Figure 3
Effects of process parameters on density. a. Laser power. b. Scanning speed. c. Wire feed speed. d. Shielding gas pressure.

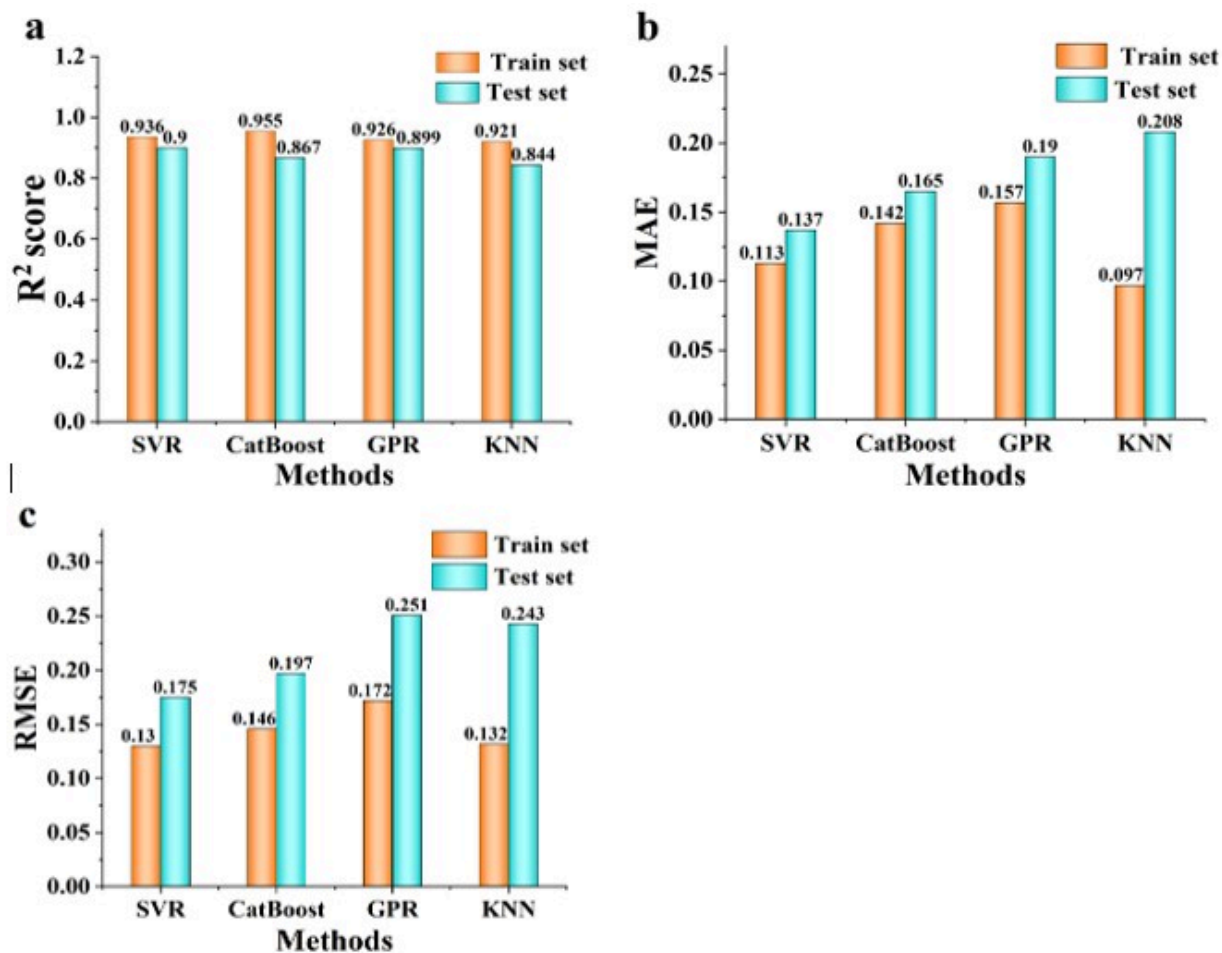


Figure 4

Evaluation results of the four models. a. R² score. b. MAE. c. RMSE.

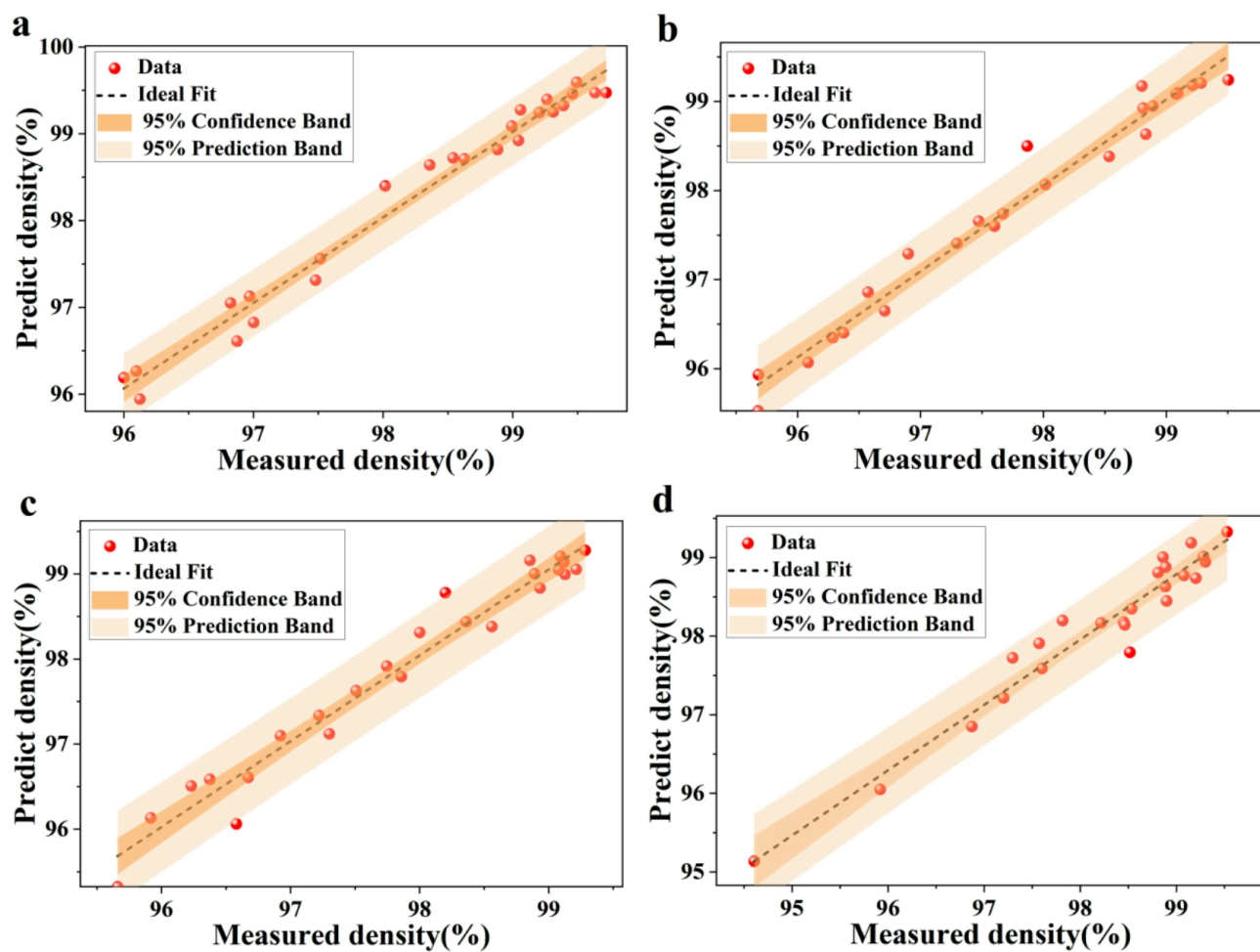


Figure 5

Comparison of observed and predicted values for the four models. a. SVR. b. CatBoost. c. GPR. d. KNN.

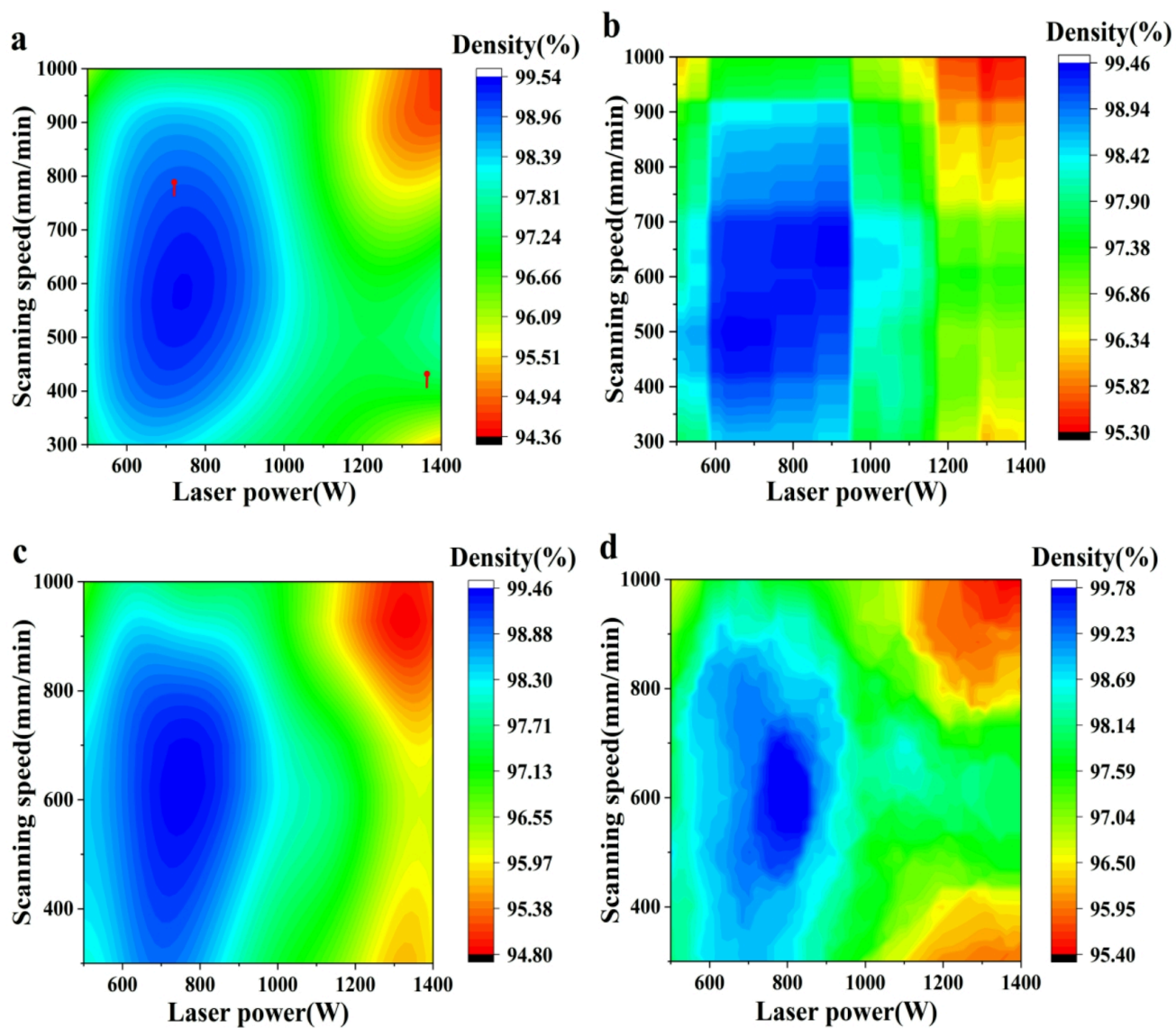


Figure 6

Contour plots of the four models. a. SVR. b. CatBoost. c. GPR. d. KNN.

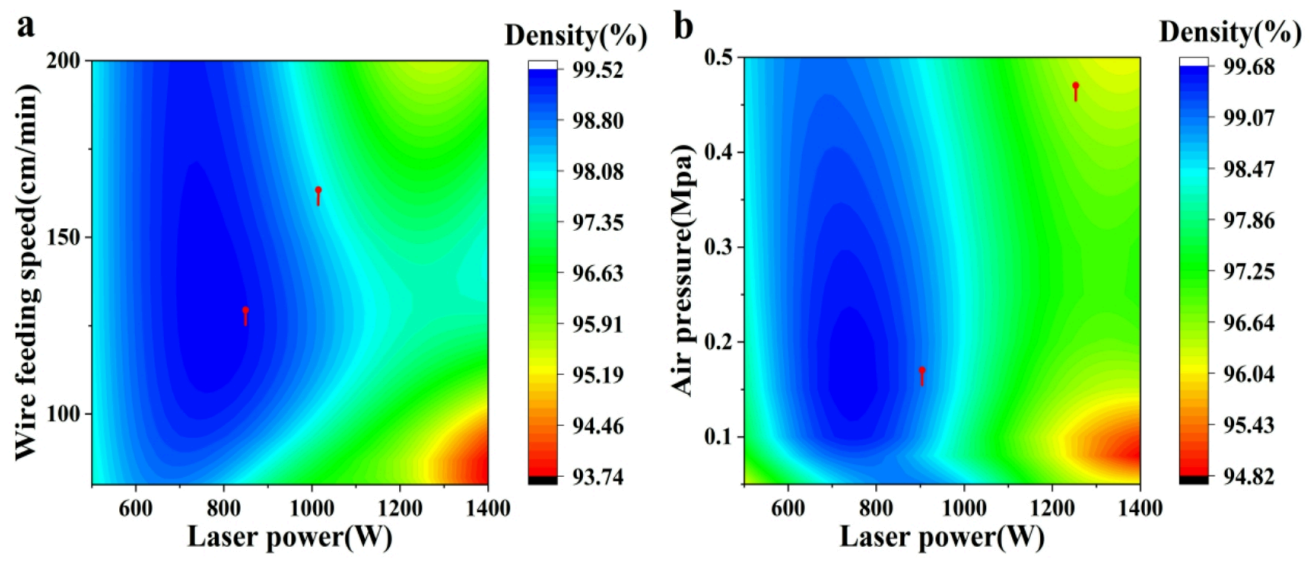


Figure 7

Predicted contour plots of the SVR model. a. Scanning speed 600 mm/min, air pressure 0.2 MPa. b. Scanning speed 600 mm/min, wire feed speed 160 cm/min.