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Quantitative Analysis of Process Parameter Effects on Deposition Layer Geometry in DED Additive Manufacturing

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Abstract: In laser-directed energy deposition (DED), the geometric characteristics of individual deposited layers—height (H) and width (W)—fundamentally determine the dimensional accuracy of final components. This study quantifies the effects of three key process parameters—laser power, scanning speed, and powder feed rate—on H and W to establish a quantitative basis for dimensional control. A full factorial design (5×4×3) was employed, generating 60 single-track samples. Three-way ANOVA was applied to identify significant factors, quantify contribution ratios, and examine interactions. Results show excellent model fit (H: R^2=96.47%, W: R^2=97.51%). For height H, powder feed rate dominates (57% contribution), followed by scanning speed (31%), while laser power shows no significant effect ($P>0.05$). For width W, laser power dominates (60%), followed by scanning speed (28%). A significant interaction exists between scanning speed and powder feed rate for width ($P<0.001$): at low speeds (<11.5 mm/s), increasing feed rate increases W; at high speeds (>11.5 mm/s), the opposite occurs. These findings reveal distinct parameter dominances—feed rate controls height, power controls width—providing a quantitative foundation for targeted parameter optimization in DED processes.

Keywords: Directed Energy Deposition; Deposition Layer Geometry; Process Parameters; ANOVA.

1. Introduction

(1) Research Background

In recent years, quality problems have become critical challenges for manufacturing enterprises worldwide. To address these challenges, many countries have proposed relevant policies promoting high-quality manufacturing, such as "Made in China 2025" which emphasizes "quality first" as the lifeline of manufacturing transformation.[1] Quality control, which systematically monitors and improves production processes to ensure products consistently meet requirements, is fundamental for enterprise competitiveness.[2]

Additive manufacturing (AM), particularly directed energy deposition (DED), has gained significant attention due to its design freedom, material efficiency, and ability to fabricate complex components.[3,4] According to statistics, the global AM industry grew from \$5.29 billion in 2003 to \$18 billion in 2022, with a CAGR of 19.58% .[5] China's AM industry expanded from 1 billion yuan in 2012 to 32 billion yuan in 2022 .[5]

(2) Quality Challenges in DED

Despite its potential, industrial adoption of DED is hindered by quality issues.[4,6]The inherent "melt-solidification" cycle creates large thermal gradients, leading to dimensional deviations, porosity, and cracking .[7] Among these, dimensional accuracy is particularly critical for aerospace and automotive components where tight tolerances are essential.[8] For example, in engine manifold manufacturing—a key DED application—dimensional deviations in pipe diameters can cause assembly difficulties, gas leakage, and even engine failure. Production data from Company D shows the pass rate for manifold pipe diameters (deviation ≤ 0.65 mm) was only 78.4%, far below customer requirements.

(3) The Role of Deposition Layer Geometry

In DED, the geometric characteristics of individual deposited layers—height (H) and width (W)—are the fundamental building units that determine final component dimensional accuracy.[9] As shown in Figure 1, a single-track deposition layer exhibits a characteristic cross-sectional profile. Precise control of H and W is the prerequisite for achieving high-precision dimensional control. When layers are stacked, variations in H accumulate vertically, while variations in W affect lateral dimensions. Understanding quantitative relationships between process parameters and these geometric features is essential for scientific process optimization.

(4) Literature Review

Scholars have extensively studied additive manufacturing parameter optimization. Xu et al. found that in laser-arc hybrid AM, deposition width positively correlated with laser power and negatively correlated with scanning speed, with arc current having the most significant impact.[8] Kladovasilakis et al. emphasized that understanding parameter-layer geometry relationships is crucial for high-precision manufacturing.[9] Kekana et al. employed ANOVA to optimize selective laser melting parameters.[3]

Regarding quality control methods, Nikolaos et al. proposed comprehensive solutions examining raw material quality, real-time monitoring, and post-process evaluation.[10] Charalampous et al, reviewed non-destructive quality control methods in AM. [11] Maucher et al. developed machine learning-based powder quality control achieving 91.3% accuracy.[12]

For dimensional accuracy, Száva et al. noted that dimensional methods in AM remain underexplored yet essential.[2] Grzegorz et al. compared measurement methods for polymer AM products.[13] Azimi et al. found that different parameters dominate different dimensional characteristics in FDM processes.[4]

(5) Research Gap

Although the above studies have discussed AM process parameters and quality control, several gaps remain: limited attention to fundamental geometric features of individual deposited layers [2]; lack of quantitative analysis of each parameter's relative contribution; frequent neglect of interaction effects [4]; and limited application to engine manifold manufacturing where dimensional accuracy critically affects performance.

(6) Objective and Scope

Therefore, this paper constructs a quantitative analysis framework based on full factorial design and ANOVA, aiming to:

Quantify the effects of laser power (P), scanning speed (Vs), and powder feed rate (Vf) on deposition layer height (H) and width (W);Identify significant parameters and quantify their contribution ratios; Characterize interaction effects between parameters; Provide a quantitative foundation for targeted parameter optimization in DED processes.

The remainder of this paper is organized as follows: Section 2 experimental data collection and design of experiments; Section 3 presents results; Section 4 discusses findings; and Section 5 concludes.

2. Experimental Data Collection and Design of Experiments

In laser additive manufacturing, the single-track deposited layer is one of the indispensable elements. Almost all DED additive manufacturing components are formed through the layer-by-layer stacking of single-track deposited layers, which ultimately creates the planar and three-dimensional structures of the part. The quality of the single-track deposited layer directly affects the dimensional accuracy and surface quality of the final printed component.

Therefore, investigating the geometric morphology of its microscopic cross-section is of critical importance. This enables analysis, from a microscopic perspective, of the process parameters that influence diameter deviation. A common research approach involves cutting the deposited layer perpendicular to the laser deposition direction, followed by measurement and analysis of the cross-sectional dimensions.

During the laser additive manufacturing process, the mechanism of melt pool formation involves the laser penetrating the powder cloud and projecting onto the substrate surface. The powder particles fall into the melt pool and gradually accumulate, ultimately forming a deposited layer. Once the melt pool solidifies, a metallurgical bonding zone is formed. Due to the high temperatures inherent in the laser additive manufacturing process, the region surrounding the melt pool undergoes microstructural changes that create distinct differences from the base material; this region is referred to as the heat-affected zone. Through this series of processes, a theoretical cross-sectional morphology of a single-track deposited layer is formed, as illustrated in the figure below:

In this figure, two important parameters are present: the height "H" and width "W" of the deposited layer. If the deposited layer is conceptualized as a segment of a circle, once the values of H and W are determined, the overall morphology of the deposited layer can be obtained. The height and width of the deposited layer are critical parameters for describing its cross-sectional geometry and represent a key focus in experimental designs investigating the effects of process parameters on single-track deposited layers.

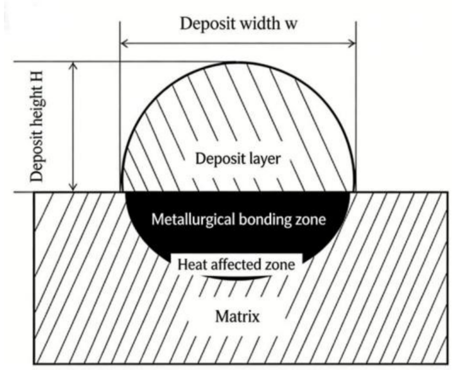

Figure 1. Schematic illustration of a single-track deposition layer cross-section

This chapter collects experimental data from samples fabricated by a company using additive manufacturing processes with varying levels of three main process parameters: laser power (P), scanning speed (Vs), and powder feed rate (Vf). The resulting deposition layer width (W) and height (H) were measured to enable subsequent multi-factor, multi-level experimental design and analysis, aiming to quantify the degree of influence each processing parameter exerts on deposition layer height and width.

Following the requirements of multi-factor, multi-level experimental design, the collected data were organized according to five levels of laser power, four levels of scanning speed, and three levels of powder feed rate, resulting in a total of 60 experimental groups. The deposition layer cross-sectional height (H) and width (W) served as the two output responses. Representative measurement results for different process parameter combinations are presented below:

Table 1. Measurement data of deposition layer height (H) and width (W) for the first 20 experimental runs.

Run	Laser power P (W)	Scanning speed Vs (mm/s)	Powder feed rate Vf (g/min)	Deposition layer height H (mm)	Deposition layer width W (mm)
1	600	8	6.3	0.882	1.570
2	650	8	6.3	0.733	1.639
3	700	8	6.3	0.783	1.790
4	750	8	6.3	0.860	1.916
5	800	8	6.3	0.943	1.893
6	600	10	6.3	0.563	1.552
7	650	10	6.3	0.672	1.661
8	700	10	6.3	0.645	1.749
9	750	10	6.3	0.676	1.785
10	800	10	6.3	0.696	1.851
11	600	12	6.3	0.471	1.465
12	650	12	6.3	0.540	1.570
13	700	12	6.3	0.588	1.668
14	750	12	6.3	0.642	1.748
15	800	12	6.3	0.618	1.838
16	600	14	6.3	0.547	1.577
17	650	14	6.3	0.500	1.555
18	700	14	6.3	0.446	1.598
19	750	14	6.3	0.493	1.749
20	800	14	6.3	0.537	1.812
18	700	14	6.3	0.446	1.598

Analysis of variance (ANOVA) is a statistical testing technique used to evaluate the significance of different input variables on output responses. It determines whether these input variables have significant effects on the response variables by comparing the variances within the data.

When addressing process improvement problems, between-group variance refers to the variation in experimental results caused by changes in input parameters, while within-group variance refers to the variation caused by random factors within the experiment. Both fall under the category of data variability. From a mathematical perspective, this involves decomposing the total variance of the experimental data into variance attributable to each parameter and variance due to random error.

The purpose of ANOVA is to decompose the total sum of squares into variation caused by factors and variation caused by error, thereby constructing an F-statistic for hypothesis testing. Typically, the null hypothesis assumes that the main effects of process parameters and their interactions have no significant influence on the response. In F-tests, the p-value method is commonly employed with a confidence level of 95%. If the p-value is less than 0.05, the null hypothesis is rejected, indicating that the process parameter has a statistically significant effect. Conversely, if the p-value is greater than 0.05, the null hypothesis cannot be rejected, meaning the process parameter has no significant effect.

Through ANOVA, not only can the magnitude of each factor's influence be determined, but the degree of experimental error can also be quantified. Furthermore, it enables identification of differences between experimental results corresponding to different factor levels, determining whether these differences arise from variations in factor levels or from experimental error. The core principle is that the overall variability of the response can be decomposed into two components: variability caused by factor level changes and variability caused by experimental error. By quantifying the influence of factors relative to error, one can determine which effects are more important.

The following sections discuss the effects of DED process parameters on deposition layer height and width, respectively.

3. Results of Process Parameter Effects on Deposition Layer Geometry

Table 2. ANOVA results for the effects of three process parameters on deposition layer height (H).

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Model	35	1.44114	0.041175	18.75	0.000
Linear	9	1.32884	0.147649	67.24	0.000
Laser power (P)	4	0.01863	0.004658	2.12	0.109
Scanning speed (Vs)	3	0.46689	0.155629	70.86	0.000
Powder feed rate (Vf)	2	0.84332	0.421661	191.99	0.000
2-Way Interactions	26	0.11230	0.004319	1.97	0.050
P × Vs	12	0.02637	0.002198	1.00	0.477
P × Vf	8	0.01948	0.002435	1.11	0.392
Vs × Vf	6	0.06645	0.011076	5.04	0.002
Error	35	1.44114	0.041175		
Total	9	1.32884	0.147649		

Note: S = 0.0468644, R^2 = 96.47%, R^2(adj) = 91.33%, R^2(pred) = 77.95%

(1) ANOVA Results for Deposition Layer Height (H)

Controlling the height of the deposited layer cross-section is critically important. Only by understanding the underlying mechanisms can a uniform deposited layer be achieved, and a stable deposited layer output is essential for the dimensional accuracy of subsequent additively manufactured components. Therefore, investigating the effects of various process parameters on deposition layer height and determining the contribution ratio of each factor is of great significance. Three-way analysis of variance (ANOVA) was performed to analyze the effects of process parameters and their interactions on deposition layer height. The results are presented in Table 2.

The Pareto chart of standardized effects for deposition layer height was generated using Minitab software to analyze the three factors and their interactions, as shown in Figure 2:

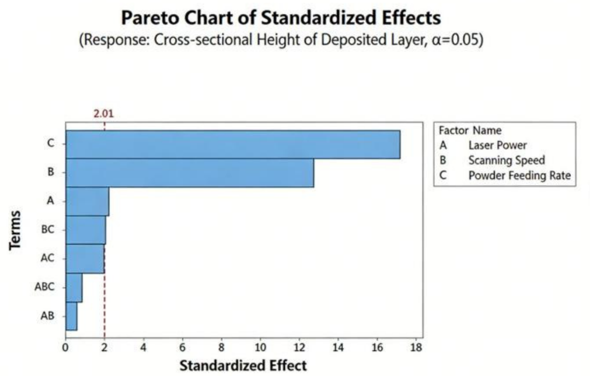

Figure 2. Pareto chart of the standardized effects for height.

The Pareto chart is used to analyze the extent to which factors influence response variation and provides an intuitive graphical representation of each factor's impact and contribution ranking. Compared with ANOVA, the generation of a Pareto chart relies on regression analysis between factors and response variables, whereby t-statistics are constructed and evaluated through t-tests of model parameters. At a 95% confidence level, the dashed line in the Pareto chart is used to compare the t-statistic with the calculated t-value to determine the importance of process parameters on the response. When a parameter's bar extends beyond the dashed line, it indicates that the parameter has a significant impact on the output. The higher the bar, the greater the contribution of that process parameter to the output. In this study, the Pareto chart was employed to validate the ANOVA results and ensure their reliability. Through the Pareto chart, the influence degree and contribution ranking of process parameters on the results can be more intuitively presented, thereby enhancing the credibility of the data analysis.

To further quantify the proportional effects of each factor, pie charts were constructed using the adjusted sum of squares (Adj SS) from the ANOVA table, providing a more intuitive visualization of the influence degree and contribution ranking, as shown in the figures below:

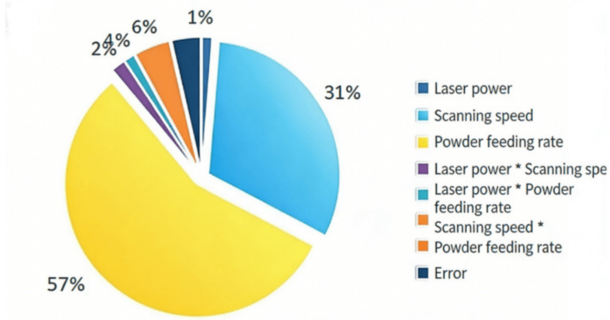

Figure 3. Contribution ratios of process parameters to deposition layer height (H) based on adjusted sum of squares.

The main effects plots for the three process parameters on deposition height are shown in Figure 4:

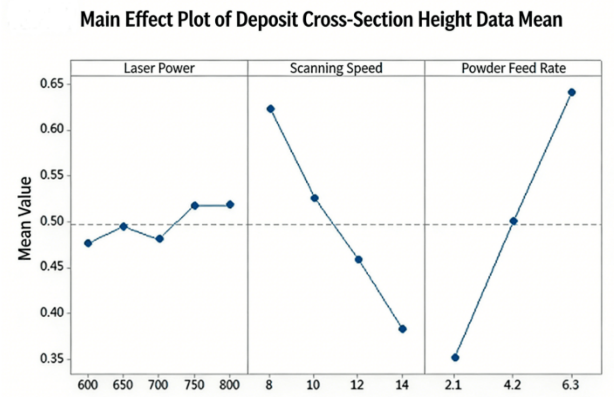

Figure 4. Main effects plots for deposition layer height (H).

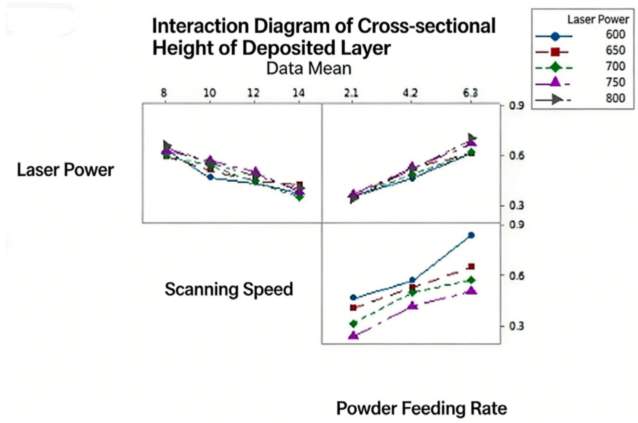

Figure 5. Main effects plots for deposition layer height (H).

Figure 5 presents the interaction plots for deposition layer height. If the influence trend of one parameter on the response varies at different levels of another parameter, this indicates an interaction effect between the two parameters.

As shown in the figure, laser power and scanning speed exhibit no significant interaction, as their lines are essentially parallel without obvious intersection. This indicates that the trend of height variation with increasing scanning speed is consistent across different laser power levels. Similarly, no significant interaction is observed between laser power and powder feed rate.

Table 3. ANOVA results for the effects of three process parameters on deposition layer width (W).

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Model	35	1.12729	0.032208	26.86	0.000
Linear	9	1.03326	0.114807	95.75	0.000
Laser power (P)	4	0.69500	0.173750	144.89	0.000
Scanning speed (Vs)	3	0.32032	0.106774	89.04	0.000
Powder feed rate (Vf)	2	0.01794	0.008969	7.48	0.003
2-Way Interactions	26	0.09403	0.003617	3.02	0.005
P × Vs	12	0.02591	0.002159	1.80	0.106
P × Vf	8	0.00693	0.000866	0.72	0.670
Vs × Vf	6	0.06119	0.010198	8.50	0.000
Error	24	0.02878	0.001199		
Total	59	1.15607			

Note: S = 0.0346290, R^2 = 97.51%, R^2(adj) = 93.88%, R^2(pred) = 84.44%

(2) ANOVA Results for Deposition Layer Width (W)

In addition to height, deposition layer width plays a crucial role in determining manufacturing efficiency. For multi-track deposition, wider tracks reduce the number of passes required to cover a given area, thereby decreasing processing time. Understanding how process parameters influence width and quantifying their relative contributions is therefore essential for optimizing both dimensional accuracy and productivity. Three-way ANOVA was performed to analyze the main effects and interactions of laser power, scanning speed, and powder feed rate on deposition width W. The results are presented in Table 3.

The three factors and their interactions were analyzed using Minitab software, and the resulting Pareto chart is shown in Figure 6:

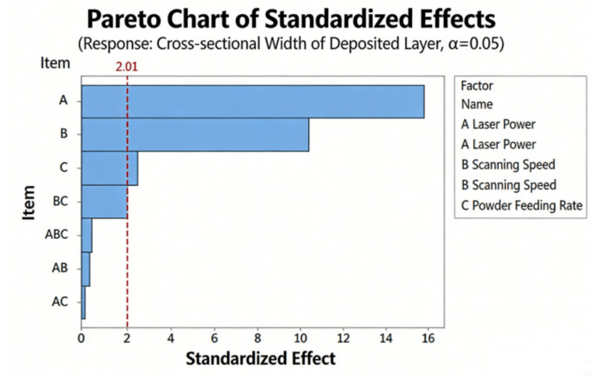

Figure 6. Pareto chart of the standardized effects for width.

The Pareto chart above clearly shows that laser power and scanning speed have the most significant effects on deposition layer cross-sectional width.

To further quantify the proportional effects of each factor on width, the adjusted sum of squares (Adj SS) values from the ANOVA table were used to determine the contribution ratios. A pie chart illustrating the significant factor contributions for width was constructed, as shown in Figure 7:

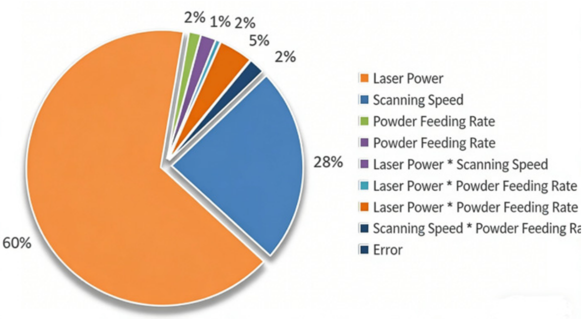

Figure 7. Contribution ratios of process parameters to deposition layer width (W) based on adjusted sum of squares

The main effects plots for the three process parameters on deposition width are shown in Figure 8:

As shown in the interaction plots in Figure 9, laser power and scanning speed, as well as laser power and powder feed rate, exhibit no significant interaction effects, as evidenced by their parallel or nearly parallel lines. In contrast, the interaction plot between scanning speed and powder feed rate reveals clear intersection points at scanning speeds of 10 mm/s and 12 mm/s with powder feed rates of 2.1 g/min and 4.2 g/min, with the response exhibiting different trends across parameter combinations.

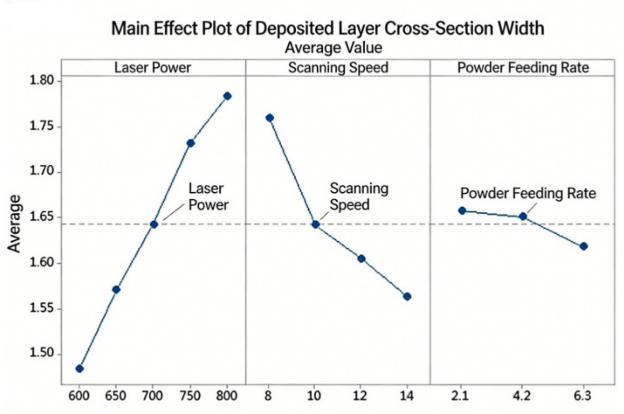

Figure 8. Main effects plots for deposition layer width (W).

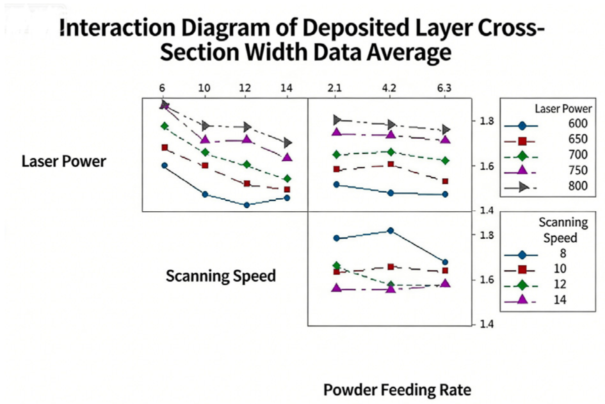

Figure 9. Main effects plots for deposition layer width (W).

This indicates a significant interaction between scanning speed and powder feed rate, with the two characteristic lines intersecting at a scanning speed of approximately 11.5 mm/s. In the low-speed regime (<11.5 mm/s), increasing the powder feed rate increases deposition width; while in the high-speed regime (>11.5 mm/s), increasing the powder feed rate decreases deposition width.

This finding demonstrates that these two parameters must be optimized synergistically rather than adjusted independently, providing valuable guidance for companies seeking to achieve stable product quality characteristics through optimized process parameters.

4. Discussion

(1) Analysis of Deposition Layer Height (H)

As shown in Table 2, the model F-value of 18.75 with $P < 0.05$ indicates that the model is statistically significant. The regression coefficient R^2 presented in the notes below the table shows that the regression model explains 96.47% of the variation in deposition layer height. The R^2 value is also very close to unity, indicating that the model effectively captures the relationship between deposition layer height and the process parameters.

The P-values for scanning speed, powder feed rate, and their interaction are all less than the significance level of 0.05. Therefore, from a statistical perspective, scanning speed and powder feed rate have the greatest influence on height. In contrast, the P-value for laser power is 0.109, which exceeds the 0.05 significance level, indicating that its effect on deposition layer height is not statistically significant.

As shown in Figure 3, powder feed rate accounts for 57% of the variation in height, making it the most important parameter affecting deposition height. Scanning speed contributes 31%, ranking as the second most important parameter, while only 1% of the variation in deposition height is attributable to laser power. Figure 2 also reflects that powder feed rate and scanning speed have the most significant effects on deposition layer cross-sectional height, which is consistent with the results shown in Figure 3.

Figure 4 illustrates that the greatest influence on deposition layer height occurs at a laser power of 800 W, a scanning speed of 8 mm/s, and a powder feed rate of 6.3 g/min. At a powder feed rate of 6.3 g/min, the effect on height is substantially above the mean level, followed by scanning speed, and finally laser power. Changes in laser power have no significant effect on height; it can be stated that height values are nearly identical across the 600-800 W power range.

This phenomenon can be explained as follows: as laser power continuously increases, the linear energy input also increases, which will generate a larger melt pool on the substrate. However, when the powder feed rate remains constant, the deposition layer growth rate does not increase substantially. Therefore, controlling the laser power range is also necessary; otherwise, a certain degree of waste may occur.

(2) Analysis of Deposition Layer Width (W)

The regression coefficient R^2 indicates that the model explains 97.51% of the variance in deposition layer width, demonstrating a good model fit. The model F-value of 26.86 with $P < 0.05$ confirms that the model is statistically significant. Furthermore, the R^2 value is very close to unity, indicating that the adopted model effectively reflects the relationship between deposition layer cross-sectional width and the three process parameters. The model's standard error is only 0.032, which demonstrates the accuracy of the model.

Analysis of the P-values reveals that laser power, scanning speed, powder feed rate, and the interaction between scanning speed and powder feed rate all have statistically significant effects on deposition layer width, with all P-values less than 0.05.

As shown in the figure 7, laser power accounts for 60% of the variation in deposition layer cross-sectional width, making it the most important factor determining width. Scanning speed is the second most significant factor, contributing 28%. Among all factors, only 2% of the variation is attributable to powder feed rate. This finding is consistent with the conclusions presented in Figure 6.

Figure 8 shows that the greatest influence on deposition layer width occurs at a laser power of 800 W, a scanning speed of 8 mm/s, and a powder feed rate of 2.1 g/min. At a laser power of 800 W, the effect on width is substantially above the mean level, followed by scanning speed, and finally powder feed rate. Changes in powder feed rate have almost no significant effect on the mean width value, indicating that across the three powder feed rates—2.1 g/min, 4.2 g/min, and 6.3 g/min—width shows almost no obvious change and remains near its mean value.

(3) Practical Implications for DED Process Control

The quantitative findings of this study provide actionable guidance for controlling deposition layer geometry in DED processes, with direct relevance to industrial applications such as the J-type engine manifold manufacturing that motivated this research.

Targeted Parameter Adjustment Strategy:

The contribution ratios derived from ANOVA reveal a clear division of labor among the three process parameters. Powder feed rate dominates height variation (57%), laser power dominates width variation (60%), and scanning speed significantly influences both dimensions (31% for height, 28% for width). This quantification enables manufacturers to adopt a targeted approach to parameter adjustment based on specific quality objectives.

When the goal is to modify deposition height, powder feed rate should be the primary adjustment variable. Increasing powder feed rate directly increases the amount of material deposited per unit time, leading to greater layer thickness. Scanning speed can serve as a secondary adjustment—reducing scanning speed further enhances height by increasing the material deposition per unit length. Importantly, laser power adjustments can be largely ignored when height control is the sole objective, as this parameter explains virtually none of the height variation.

Conversely, when width control is the priority—such as in engine manifold manufacturing where pipe diameter accuracy is critical—laser power becomes the primary control variable. Higher laser power increases energy input, creating larger melt pools that spread more extensively before solidification, resulting in wider tracks. Scanning speed again serves as a secondary adjustment, with lower speeds allowing more time for lateral spreading. Powder feed rate adjustments have minimal direct effect on width and should not be relied upon for width control.

For applications requiring simultaneous control of both dimensions—for example, maintaining a specific aspect ratio while adjusting build rate—scanning speed emerges as the critical parameter. Because scanning speed significantly affects both height and width, it provides a means to influence both dimensions simultaneously. However, its involvement in significant interactions means that its effects cannot be considered in isolation.

Managing Parameter Interactions:

The significant interaction identified between scanning speed and powder feed rate for width has important practical implications. The interaction reveals a critical threshold at approximately 11.5 mm/s, below which increasing feed rate increases width, and above which increasing feed rate decreases width. This non-linear behavior means that the same adjustment to powder feed rate can produce opposite effects on width depending on the scanning speed regime.

For process optimization, this finding suggests a two-step approach. First, the desired scanning speed regime should be established based on productivity requirements and thermal considerations. If high productivity is needed, operating in the high-speed regime (>11.5 mm/s) may be preferable, but manufacturers must be aware that increasing feed rate in this regime will actually decrease width—potentially causing under-sizing of features. Conversely, if width control is critical, operating in the low-speed regime (<11.5 mm/s) provides more predictable behavior where feed rate increases produce width increases.

Second, within the chosen regime, powder feed rate can be adjusted to achieve target height while anticipating the width response based on the regime. This coordinated adjustment strategy enables manufacturers to balance productivity and precision objectives more effectively than independent parameter tuning.

Application to Engine Manifold Manufacturing:

Returning to the motivating industrial problem—dimensional deviations in J-type engine manifold pipe diameters—these findings provide a scientific foundation for process optimization. The manifold pipe diameter is primarily determined by the cumulative width of deposited layers, making width control the primary quality objective.

For manifold production, manufacturers should prioritize laser power adjustment as the primary means of width control. Increasing laser power will produce wider tracks, directly increasing pipe diameter, while decreasing power will reduce diameter. Scanning speed should be used as a secondary adjustment, recognizing that changes will affect both width and height. If height adjustments are needed—for example, to optimize build time or material usage—powder feed rate should be the primary control variable, with careful attention to the scanning speed regime to anticipate width effects.

The identified interaction between scanning speed and powder feed rate is particularly relevant for manifold production. If a manufacturer attempts to increase productivity by increasing both scanning speed and powder feed rate simultaneously, the effect on pipe diameter will depend on where the operating point lies relative to the 11.5 mm/s threshold. Above this threshold, the width-reducing effect of increased speed may be compounded by the width-reducing effect of increased feed rate, potentially causing severe under-sizing. Below the threshold, increased speed reduces width while increased feed rate increases width, potentially canceling each other out.

Broader Implications for Additive Manufacturing Quality Control

Beyond the specific application to engine manifolds, these findings contribute to the broader goal of transitioning additive manufacturing from an empirical "trial-and-error" approach to a science-based, data-driven discipline. The quantification of parameter contribution ratios provides a rational basis for process optimization that can be applied across different materials, component geometries, and quality requirements.

For companies implementing DED technology, these results suggest that effective quality control requires understanding not just which parameters are significant, but how much each parameter contributes to specific quality characteristics. This understanding enables: More efficient process development by focusing experimental efforts on the most influential parameters; More robust process control by identifying which parameters require tight monitoring; More predictable quality outcomes by anticipating the effects of parameter adjustments

By moving from qualitative trend descriptions ("increasing power increases width") to quantitative guidance ("laser power contributes 60% to width variation"), manufacturers can make more informed decisions about resource allocation for process optimization and quality improvement initiatives.

Economic and Operational Benefits:

Implementing these parameter optimization guidelines can yield significant economic and operational benefits. Reduced dimensional variability leads to lower rejection rates, decreasing material waste and rework costs. More efficient process development reduces the number of trial runs required to establish stable parameter windows, saving machine time, material, and labor. Improved dimensional consistency enhances customer satisfaction and reduces the risk of field failures, protecting brand reputation and reducing warranty costs.

For high-value components such as aerospace or automotive parts, where dimensional accuracy directly affects performance and safety, the benefits of improved process control extend beyond cost savings to include enhanced product reliability and regulatory compliance.

(4) Limitations of This Study

Several limitations should be considered when interpreting and generalizing the findings of this study.

Single-Track, Single-Layer Focus:

This study investigated single-track, single-layer deposits, which represent the fundamental building units of DED components. However, actual components involve multi-track, multi-layer deposition with complex thermal histories and inter-layer interactions. Factors such as inter-layer dwell time, substrate heating from previous layers, and track overlapping may introduce additional effects not captured in single-track studies. Future work should extend this analysis to multi-layer builds to validate the applicability of these findings to actual components.

Single Material System:

The experiments were conducted using a single material system. Different materials possess different thermal properties (thermal conductivity, melting point, specific heat), melt pool dynamics, and solidification behaviors, which may alter the relative importance of process parameters. The quantitative contribution ratios reported here may not directly transfer to other materials without validation.

Limited Parameter Range:

The parameter ranges were selected based on typical processing windows for the material studied. Conclusions about significance and contribution ratios are valid only within these ranges. Extrapolation to parameter values outside the tested ranges (e.g., laser power >800 W or <600 W) should be approached with caution, as non-linear behaviors may emerge.

Static Measurements:

The measurements of H and W were performed on cooled, solidified samples. These post-process measurements do not capture dynamic melt pool behavior during deposition. In-situ monitoring techniques such as high-speed imaging or pyrometry could provide additional insights into the mechanisms underlying the observed parameter effects.

Uncontrolled Factors:

Factors such as powder particle size distribution, substrate temperature, and ambient conditions were controlled but not systematically varied. These factors may interact with the studied parameters and influence deposition geometry, representing potential sources of unexplained variation in the models.

5. Conclusion

(1) Summary of Findings

This study systematically investigated the effects of three key process parameters—laser power, scanning speed, and powder feed rate—on deposition layer geometry in laser-directed energy deposition (DED) additive manufacturing. A full factorial experimental design (5 × 4 × 3) was employed, generating 60 single-track samples. Three-way analysis of variance (ANOVA) was applied to identify significant factors, quantify contribution ratios, and examine interaction effects. The main findings are summarized as follows.

Parameter Effects on Deposition Layer Height (H):

The ANOVA results revealed that powder feed rate is the dominant factor controlling deposition height, contributing 57% to the total variation. Scanning speed also significantly affects height, with a contribution ratio of 31%. In contrast, laser power shows no statistically significant effect on height ($P > 0.05$), contributing only 1% to height variation. The interaction between scanning speed and powder feed rate is significant for height ($P = 0.002$), while interactions involving laser power are not significant. The main effects plot for height demonstrates a strong positive correlation with powder feed rate and a strong negative correlation with scanning speed, while laser power exhibits a nearly flat response across the tested range.

Parameter Effects on Deposition Layer Width (W):

For deposition width, a distinctly different pattern emerges. Laser power dominates width variation with a contribution ratio of 60%, making it the primary control parameter. Scanning speed is the second most significant factor, contributing 28%. Powder feed rate, while statistically significant, contributes only 2% to width variation. Similar to the height results, the interaction between scanning speed and powder feed rate is highly significant for width ($P < 0.001$), while interactions involving laser power are not significant. The main effects plot for width shows a strong positive correlation with laser power, a moderate negative correlation with scanning speed, and minimal response to powder feed rate changes.

Interaction Effects:

A significant interaction between scanning speed and powder feed rate was identified for both height and width, with particularly pronounced effects on width. The interaction plots reveal a critical threshold at approximately 11.5 mm/s for width. Below this scanning speed (low-speed regime), increasing powder feed rate increases deposition width. Above this threshold (high-speed regime), increasing powder feed rate decreases deposition width. This non-linear behavior has important implications for process optimization, as the same parameter adjustment can produce opposite effects depending on the operating regime.

Model Validation:

The ANOVA models demonstrated excellent fit, with R^2 values of 96.47% for height and 97.51% for width. Residual analysis confirmed that all ANOVA assumptions—normality, homogeneity of variance, and independence—were satisfied, validating the statistical reliability of the conclusions.

(2) Key Contributions

This study makes several contributions to the understanding and practice of DED additive manufacturing.

Quantification of Parameter Contribution Ratios:

Beyond identifying statistically significant parameters, this study provides quantitative contribution ratios for each parameter's influence on deposition geometry. For height, powder feed rate (57%), scanning speed (31%), and laser power (1%) establish a clear hierarchy of importance. For width, laser power (60%), scanning speed (28%), and powder feed rate (2%) demonstrate an equally clear but different hierarchy. This quantification enables prioritized parameter adjustment—manufacturers can focus their optimization efforts on the parameters that matter most for each specific geometric feature, rather than relying on qualitative trend descriptions or trial-and-error approaches.

Identification and Characterization of Interaction Effects:

The significant interaction between scanning speed and powder feed rate, including the identification of a critical speed threshold (~11.5 mm/s), reveals non-linear behavior that cannot be captured by single-factor experiments. This finding demonstrates that parameter effects in DED processes are not simply additive—the influence of one parameter depends on the level of another. The characterization of this interaction provides specific guidance for coordinated parameter adjustment, enabling more precise control than independent parameter tuning.

Dimension-Specific Parameter Dominance:

The finding that different parameters dominate different geometric dimensions establishes that deposition layer geometry cannot be controlled by a single "master parameter." Height is primarily mass-limited, controlled by powder feed rate. Width is primarily energy-limited, controlled by laser power. Scanning speed serves as a dual-purpose parameter, significantly affecting both dimensions. This dimension-specific dominance has fundamental implications for process understanding and provides a scientific basis for targeted control strategies depending on which geometric characteristic is most critical for the application.

Scientific Foundation for Industrial Application:

By connecting fundamental parameter analysis to the practical problem of engine manifold dimensional accuracy, this research demonstrates how quantitative understanding can address real manufacturing quality challenges. The findings provide a rational basis for moving from empirical parameter selection toward data-driven process optimization, ultimately improving dimensional consistency and reducing rejection rates in production environments.

(3) Recommendations for Future Work

Based on the findings and limitations of this study, several directions for future research are proposed.

Extension to Multi-Track, Multi-Layer Deposition:

Future studies should investigate whether the parameter effects identified for single-track deposits persist in multi-track, multi-layer components. Factors such as inter-layer dwell time, substrate heating from previous layers, and track overlapping may introduce additional complexities that modify the relationships quantified in this study. Understanding these effects is essential for translating fundamental findings to actual component manufacturing.

Material System Generalization:

Similar studies should be conducted for different material systems commonly used in DED applications, including titanium alloys, nickel-based superalloys, aluminum alloys, and tool steels. Different materials possess different thermal properties, melt pool dynamics, and solidification behaviors, which may alter the relative importance of process parameters. Developing material-specific contribution databases would enable more precise parameter selection across diverse applications.

Expanded Parameter Ranges and Additional Parameters:

Future work could explore wider parameter ranges and include additional process parameters such as laser spot size, beam profile, powder particle size distribution, substrate preheating temperature, and shielding gas flow rate. Response surface methodology could be employed to develop predictive models for geometry as a function of multiple parameters, enabling more comprehensive process optimization.

Integration with In-Situ Monitoring:

Incorporating in-situ monitoring techniques such as high-speed imaging, pyrometry, or optical emission spectroscopy could provide real-time data on melt pool dynamics during deposition. Correlating in-situ measurements with post-process geometry could reveal the underlying physical mechanisms responsible for the observed parameter effects, enabling deeper understanding and more robust process control.

Development of Predictive Models:

The quantitative understanding developed in this study provides a foundation for predictive modeling of deposition geometry. Machine learning approaches, such as neural networks or gradient boosting algorithms, could be trained on experimental data to predict height and width from process parameters. Such models would enable real-time quality prediction and closed-loop control in production environments, moving from reactive quality inspection to proactive quality assurance.

Validation with Industrial Components:

Finally, the optimization guidelines derived from this fundamental study should be validated by applying them to actual industrial components, such as the J-type engine manifold that motivated this research. Demonstrating improved dimensional consistency and reduced rejection rates in production would confirm the practical value of this approach and facilitate technology transfer to manufacturing environments.

In conclusion, this study provides a quantitative foundation for understanding and controlling deposition layer geometry in DED additive manufacturing. The findings enable more rational process optimization, contribute to fundamental understanding of parameter effects, and offer practical guidance for improving dimensional accuracy in critical applications such as engine manifold production.

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