Investigation on Surface Quality in a Hybrid Manufacturing System Combining Wire and Arc Additive Manufacturing and Machining

Fang Li, Shujun Chen, Junbiao Shi and Hongyu Tian

Abstract Wire and arc additive manufacturing (WAAM) has gained popularity in recent years due to its unique efficiency and cost advantages. Nevertheless, due to the stair-stepping effect and the liquidity of molten metal, the achieved geometric accuracy and surface quality are still very limited. The combination of WAAM and machining, namely hybrid manufacturing, provides a fundamental solution to the above problem. Because machining is performed after depositing several layers, the deposition width, deposition height, and surface waviness have great effects on the machined surface quality, in addition to the machining parameters including spindle speed and feedrate. In this paper, the dependence of the machined surface quality (characterized by surface roughness) on the influencing factors mentioned above is investigated based on quadratic general rotary unitized design (QGRUD). To reduce the number of experiments, a comprehensive factor, namely material removal area (MRA), is introduced to characterize the deposition width, deposition height, and surface waviness. The analysis results show that spindle speed is the most influential factor, followed by MRA and feedrate. Furthermore, a high spindle speed and a moderate feedrate are preferred, which contribute to not only improving the surface quality and the efficiency but also reducing the demand of geometric accuracy for WAAM.

Keywords Hybrid manufacturing · Wire and arc additive manufacturing
Machining · Surface roughness · Parametric optimization

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1 Introduction

Metallic additive manufacturing (AM) techniques can be broadly categorized depending on how the feedstock is supplied (powder bed, powder feeding and wire feeding) and which energy source is selected (electron beam, laser, and arc) [1, 2]. Among them, wire and arc additive manufacturing (WAAM) [3, 4], employing metal wire as the feedstock and welding arc as the heat source, has drawn increasing research interest in recent years. It offers various advantages such as high productivity, low cost, high material utilization, high energy efficiency, and safe operation. These advantages make WAAM highly competitive in fabricating medium to large-scale metal parts. Nevertheless, its inherent drawbacks, i.e., low geometric accuracy and poor surface quality due to the stair-stepping effect and the liquidity of molten metal, greatly limit its application in high-precision occasions. The combination of WAAM and machining, namely hybrid manufacturing, provides a fundamental solution to the above problem [5]. It enables material depositing and surface finishing to be achieved in a single setup, thereby making the best use of the strengths of both processes while avoiding their limitations. Several effects have been made to develop hybrid manufacturing systems in recent years [6–10].

The hybrid manufacturing system studied in this paper is illustrated in Fig. 1. Both the side and the top surfaces are machined after depositing several layers, followed by subsequent addition and subtraction steps until the final part is created. Only the quality of the side surface is concerned in this paper because the top surface will be covered by the subsequent layers. It can be observed from Fig. 1 that the axial cutting depth during machining is determined by the product of the layer thickness and the number of layers, i.e., deposition height, whereas the radial cutting depth is determined by the deposition width minus the target width as well as the surface waviness. Specifically, the surface waviness is in the form of peaks

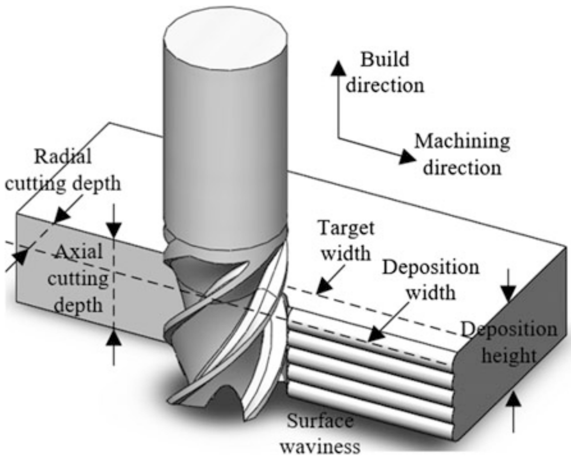

Fig. 1 Schematic diagram of a hybrid manufacturing system

and valleys resulting from the stair-stepping effect. Therefore, all of the deposition width, deposition height, and surface waviness have great effects on the machined surface quality. In addition, the machining parameters such as spindle speed and federate also have effects on the machined surface quality. As a consequence, it is more challenging to assess surface quality in a hybrid manufacturing system compared with individual machining systems.

Surface roughness (R_a) is commonly used to indicate surface quality, which is related to the part functional performance in terms of fatigue, corrosion resistance, creep life, etc. Generally, surface roughness depends on several factors, such as spindle speed, feedrate, radial and axial cutting depths, tool material and geometry, tool wear, etc. [11]. There have been numerous studies conducted on the prediction of surface roughness and the optimization of process parameters. Oktem et al. [12] applied a Taguchi optimization method to find the optimal process parameters which minimize surface roughness when milling the mold surfaces of 7075-T6 aluminum material. Kilickap et al. studied the influence of machining parameters on the surface roughness obtained in drilling of AISI 1045 and developed a mathematical prediction model using response surface methodology (RSM) [13]. Oktem et al. [14] developed an artificial neural network (ANN) to predict the surface roughness and applied the genetic algorithm to determine optimum cutting parameter leading to minimum surface roughness.

This paper aims to investigate the dependence of the machined surface quality, characterized by surface roughness, on the main influencing factors including deposition width, deposition height, surface waviness, spindle speed, and feedrate mentioned above, and provide a guide to optimize these process parameters in the hybrid manufacturing system. The quadratic general rotary unitized design (QGRUD) is adopted, which is a regression method with rotation and versatility, thus enabling one to reduce the number of experiments and get more accurate results [15]. Besides, a comprehensive factor, namely material removal area (MRA), is introduced to characterize the deposition width, deposition height, and surface waviness. Thus, the influencing factors involved reduced from five to three, i.e., spindle speed, feedrate and MRA, and thereby the required number of experiments is much less.

2 System Description

A hybrid manufacturing system combining WAAM and machining has been developed at Beijing University of Technology (BJUT), as shown in Fig. 2. It is based on a two-robot cooperative platform. One robot is IGM RTI2000, equipped with two Fronius Synergic 5000 welding machines to implement Tandem GMAW (gas metal arc welding)-based WAAM. In Tandem GMAW, two welding wires are passed through the same welding torch, thus providing much higher productivity than conventional GMAW. The other robot is KUKA KR500, which is a heavy-duty robot that is suitable for milling applications. It is equipped with a

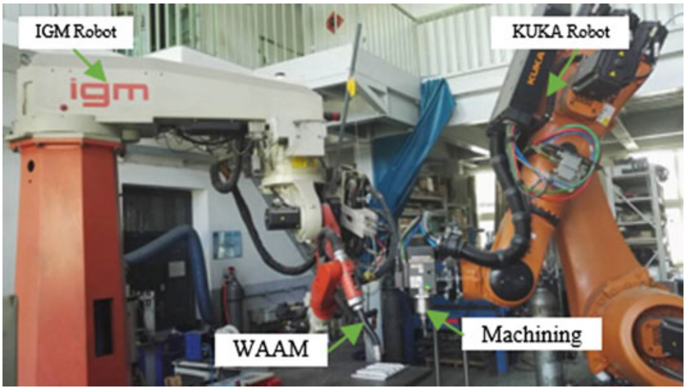

Fig. 2 Hybrid manufacturing system based on a two-robot cooperative platform

high-speed electric spindle ES779 with a maximum spindle speed of 22,000 rpm. The wire material used is Al2325 alloy with the chemical composition of Cu 3.9–4.8%, Mn 0.1–1.0%, Ti 0.15%, Mg 0.4–0.8%, Zn 0.3%, etc., in addition to Al. The substrate material is Al2219 alloy. Aluminum alloy has wide applications in civil aviation and automobile industry due to light weight and favorable properties.

3 Methods

3.1 Definition of Material Removal Area (MRA)

As mentioned above, five factors affecting the surface roughness, i.e., deposition width, deposition height, surface waviness, spindle speed, and feedrate, are considered. If the QGRUD is applied directly, 64 sets of experiments are required, which are extremely time-consuming. In this paper, a comprehensive factor, namely MRA, is introduced to characterize the deposition width, deposition height, and surface waviness. Thus, the factors involved reduced from five to three and the required number of experiments is reduced to 20 according to QGRUD. MRA is defined as the sectional area of the region that needs to be removed, as illustrated in Fig. 3. The effects of the three factors on the surface roughness can be reflected through MRA. It is also known that MRA is an indicator of the geometric accuracy of the WAAM process. The higher the geometric accuracy, the lower the MRA.

From Fig. 3, we know that MRA can be calculated as follows:

$$\mathrm{MRA} = N \times (W_0 \times H_0 + \partial \times W_1 \times H_0) \tag{1}$$

where N denotes the number of layers, H_0 denotes the layer thickness, W_0 denotes the deposition width minus the target width and W_1 denotes the maximum distance between the peaks and the valleys on the surface. The coefficient ∂ is determined to 0.7 based on preliminary experiments. Generally, N is fixed in practice, i.e., the WAAM process and the machining process are alternated every N layers. In this paper, N is set to 6.

3.2 Design of Experiments

To apply QGRUD, the predominant factors affecting the response should be identified and their upper and lower limits should be determined first. In this paper, spindle speed (A), feedrate (B), and MRA (C) are identified as the predominant factors and surface roughness (R_a) is the response. The lower and upper limits of these factors are determined as seen in Table 1, which are divided into five levels coded by −1.6817, −1, 0, +1 and +1.6817 according to QGRUD.

The 3-factor-5-level QGRUD requires 20 sets of experiments in total, 8 as factorial points, 6 as star points, and 6 as center points. The resulting design matrix is generated, as given in Table 2.

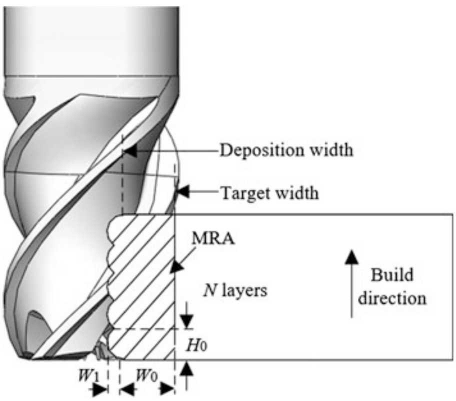

Fig. 3 Illustration of MRA

Table 1 Coding for factor and level

Symbol	Parameter	Level				
		−1.68	−1	0	1	1.68
A	Spindle speed (rpm)	1000	2400	4500	6600	8000
B	Feedrate (mm/s)	1	1.8	3	4.2	5
C	MRA (mm^2)	10	14	20	26	30

Table 2 Experimental design matrix and the response

Exp. No.	Coding (*A B C*)	Roughness (μm)	Exp. No.	Coding (*A B C*)	Roughness (μm)
1	(−1−1 −1)	1.75	11	(0 − 1.682 0)	1.76
2	(1 − 1 −1)	1.36	12	(0 1.682 0)	1.86
3	(−1 1 − 1)	1.95	13	(0 0 − 1.682)	1.65
4	(1 1 − 1)	1.52	14	(0 0 1.682)	1.78
5	(−1−1 1)	1.99	15	(0 0 0)	1.59
6	(1 − 1 1)	1.51	16	(0 0 0)	1.65
7	(−1 1 1)	2.11	17	(0 0 0)	1.52
8	(1 1 1)	1.81	18	(0 0 0)	1.53
9	(−1.682 0 0)	2.46	19	(0 0 0)	1.67
10	(1.682 0 0)	1.55	20	(0 0 0)	1.63

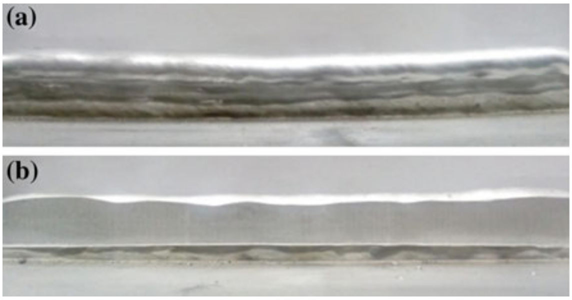

Fig. 4 Surface: **a** Surface of original wall structures (6 layers). **b** Surface after machining

3.3 *Experiments*

The experiments went through two phases. First, the WAAM experiments were carried out using the IGM RTI2000 robot to produce wall structures with 6 layers (i.e., $N = 6$), as shown in Fig. 4a. The material of the wire and the substrate has been given in Sect. 2. The travel speed was set to 0.48 m/min, the wire feedrate was set to 4.3 m/min and the welding voltage was set to 18.4 V. The shielding gas was Ar at a flow rate of 22 L/min. With the wall structures produced by WAAM, 20 sets of machining experiments were conducted then using the KUKA KR500 robot according to the experimental design matrix in Table 2, as shown in Fig. 4b. The machining tool, made of uncoated carbide alloy, had a diameter of 14 mm with a helix angle of 55°. The working mode was down milling. No cooling and lubricating agent were used. After each experiment, the surface roughness in the tool feed direction was measured using a portable roughmeter TR200 with a sensitivity of 0.01 μm. Specifically, the surface roughness was measured five times at different locations and repeated twice at each location. The average value was recorded, as given in Table 2.

4 Results

4.1 Regression Model

According to the experimental results given in Table 2, the quadratic regression model that describes the dependence of the surface roughness on the spindle speed (A), the feedrate (B), and the MRA (C) was obtained with the aid of the software Design-Expert 6.0 as follows.

$$R_a = 1.61 - 0.23A + 0.069B + 0.078C + 0.018AB + 0.005AC + 0.0075BC + 0.12A^2 + 0.054B^2 + 0.02C^2 \quad (2)$$

Then the variance analysis and F value testing were undertaken to validate the obtained regression model, as given in Table 3.

The F value of Lack of Fit was 4.56, lower than $F_{0.05}(5, 5) = 5.05$, indicating that Lack of Fit was not significant. The F value of the regression equation was 11.2, higher than $F_{0.05}(9, 10) = 3.137$, indicating that the regression model was significant and therefore fitted the actual system closely. Thus, we can conclude that the regression model was accurate and credible. At the level of 0.05, P values of A, B, C, and A^2 term were all lower than 0.05, which indicated that their effects on the surface roughness were significant. In contrast, P values of AB, AC, BC, and B^2 and C^2 were higher than 0.05, which indicated that their effects on the surface roughness were not significant and could be neglected. It is interesting that for any two factors, their interaction effects were not significant. After omitting the insignificant factors, the quadratic regression model was simplified to

Table 3 Variance analysis and F value testing results

Source	Sum of squares	df	Mean square	F value	P value
A	0.72	1	0.72	65.57	< 0.0001
B	0.066	1	0.066	6.02	0.0341
C	0.082	1	0.082	7.50	0.0209
AB	0.00245	1	0.00245	0.22	0.6462
AC	0.0002	1	0.0002	0.018	0.8951
BC	0.00045	1	0.00045	0.041	0.8434
A^2	0.21	1	0.21	19.27	0.0014
B^2	0.040	1	0.040	3.56	0.0885
C^2	0.004888	1	0.004888	0.45	0.5190
Model	1.10	9	0.12	11.2	0.0010
Residual	0.11	10	0.012		
Lack of fit	0.090	5	0.018	4.56	0.0607
Pure error	0.020	5	0.003937		
Total	1.21	19			

$$R_a \approx 1.61 - 0.23A + 0.069B + 0.078C + 0.12A^2 \quad (3)$$

4.2 Single Factor Effect Analysis

Based on the obtained quadratic regression model (Eq. 3), the effects of single factor on the surface roughness were analyzed, as shown in Fig. 5. It was obtained by varying one factor while keeping the other factors at zero level. It is clearly obtained that spindle speed is the dominant factor affecting the surface roughness, followed by MRA and feedrate. It is also observed the surface roughness increases with the increasing of feedrate and MRA. This is easy to understand because the material removal rate (MRR) is equal to the product of the feedrate and MRA. Higher MRR means higher cutting force and therefore higher surface roughness. On the other hand, the surface roughness decreases with increasing spindle speed because the corresponding cutting force is much lower.

4.3 Optimization

The reduction of the surface roughness can be achieved either by optimizing the MRA, i.e., the WAAM parameters or by optimizing the machining parameters. Figure 6 presents the surface roughness as a function of the spindle speed and the feedrate when the MRA is 10, 17, 24, and 30 respectively. We can conclude that

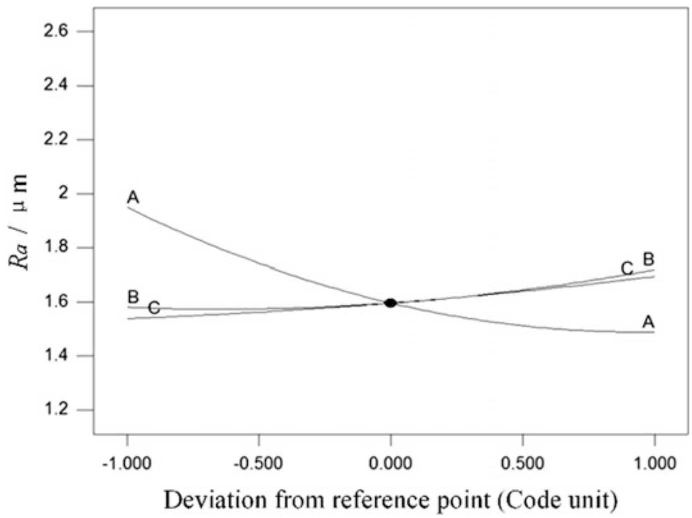

Fig. 5 Single factor effect analysis

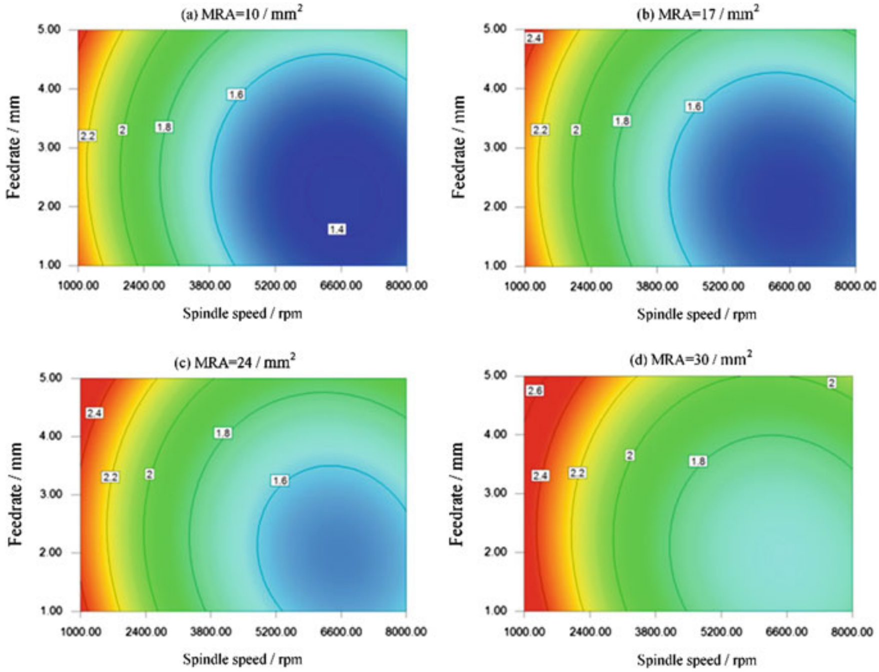

Fig. 6 Surface roughness as a function of spindle speed and feedrate when the MRA is 10, 17, 24, and 30 respectively

when the spindle speed is low, e.g., 1000 rpm, the MRA should be small enough to reduce the surface roughness. In contrast, when the spindle speed is high, e.g., 8000 rpm, no matter how large the MRA is, the surface roughness is still very small. As it is more difficult to accurately control the MRA than the other process parameters due to the liquidity of molten metal, employing a high spindle speed is very essential. It helps reduce the demand of geometric accuracy (i.e., MRA) for WAAM. Namely, if the spindle speed is quite low, the demand of geometric accuracy for WAAM is much higher. With regard to the feedrate, though lower feedrate leads to lower surface roughness, its effect is less significant than other factors. On the other hand, lower feedrate also means lower efficiency. Therefore, in order to achieve a good balance between surface quality and efficiency, a moderate feedrate is preferred. In conclusion, in order to minimize the surface roughness, increase the efficiency and reduce demand of geometric accuracy for WAAM, we expect a high spindle speed and a moderate feedrate in the hybrid manufacturing system.

5 Conclusion

A hybrid manufacturing system combining WAAM and machining has been introduced in this paper. The dependence of surface quality on deposition width, deposition height, surface waviness, spindle speed, and feedrate has been investigated based on QGRUD. From the experimental and the analysis results, the following conclusions are obtained:

1. By introducing a comprehensive factor, namely MRA, to characterize the deposition width, deposition height and surface waviness, the required number of experiments is greatly reduced.
2. Spindle speed is the most influential factor on the surface roughness, followed by MRA and feedrate. For any two factors, their interaction effects are not significant.
3. A high spindle speed is very essential for the hybrid manufacturing system, which contributes to not only improving the surface quality, but also reducing the demand of geometric accuracy for WAAM.
4. A moderate feedrate is preferred in order to achieve a good balance between the surface quality and the efficiency.

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