Predictive Modeling of Surface Roughness Based on Response Surface Methodology after WAAM

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***Abstract*—A hybrid technique of additive manufacturing and subtractive process has provided a new solution combining product design and control by software. Wire Arc Additive Manufacturing (WAAM) process wins well-respected because of its low cost and high efficiency of deposition, nevertheless the process has its limitation of high heat input and low forming accuracy. A new process of additive manufacturing with high efficiency of modeling is urgent needed which can control heat transfer, mass transfer and force transfer. To overcome the disadvantage upon, various hybrid manufacturing techniques have been developed with high efficiency and controlled modeling in recently. The machining process in hybrid manufacturing has more different characteristics from traditional material removal processes, such as residual stress and heat in the blank. These influence the whole efficiency of the hybrid manufacturing. The essential task of this paper is to explore the feasibility of thermal machining during this process and make rational use of AM in order to obtain optimal accuracy.**

Keywords—surface roughness predictive; parameters optimization; response surface methodology; WAAM

I. INTRODUCTION

The increasing requirements continuously of a sustainable, environmentally friendly and low cost are the basic needs of modern industry. While conventional manufacturing processes often pursuit a high rate of machining only. Additive Manufacturing (AM) is a technology of near net-shape components with layers by layers fashion. Due to high deposition rates and low cost equipment, wire and arc additive manufacturing by welding technology provides outstanding advantages on many light metal alloys such as aluminum alloy, titanium alloy and nickel alloy and so on.

The classification heat sources of melting the metal include gas tungsten arc welding (GTAW), plasma arc welding (PAW), and gas metal arc welding (GMAW) , which can be used to the process of wire arc additive manufacturing (WAAM) [1]. fabricating 3D metallic models of the part with WAAM can get higher density and more excellent bonding strength [2]. Nevertheless, no matter which feedback and energy source are adopted, geometric accuracy with the same level and surface quality as traditional machining processes are still difficult to fabricate because of the liquidity of molten metal and the stair-stepping effect of 3D models[3]. A hybrid of additive manufacturing and subtractive process has provided a fundamental solution to overcome the disadvantages most [4]. Various hybrid manufacturing techniques have been developed in recent years, such as layered hybrid manufacturing [5], plasma deposition hybrid milling process [6], 3D welding hybrid milling process[7], etc.

Different from the traditional machining process, such as surface contour of blank, clamping type of part and its internal performance, subtractive manufacturing process after additive manufacturing is studied and discussed in this paper. In order to obtain appropriate mechanical properties and sound geometric accuracy, subtractive process is carried out when the part is still under additive manufacturing processing waste heat. It is an important way to save energy, reduce consumption, improve product efficiency, and achieve sustainable development. Some research about thermally enhanced machining used external heat sources to heat and soften the work-piece locally in front of the cutting tool. The yield strength and work hardening of the work-piece are reduced with temperature rise at shear zone. So the plastic deformation makes hard-to-machine materials easier during machining [8].

The essential task of this paper is to predict the modelling of surface roughness of the part from WAAM and milling process. Based on response surface methodology (RSM), scientific experiments are designed to improve the feasibility of the thermal machining of 2219 aluminum alloy. For finding the optimum process parameters, some error and trial experiments are conducted remain costly[9]. Use of RSM technique can create models and prevent problems which can forecast the relation sufficiently between output parameters and input ones[10].

II. EXPERIMENTAL

A. Materials and System

Table I gives out the chemical compositions of 2219 aluminum alloy using in the experiment. A plate of 2219 aluminum alloy with the thickness of 10mm was milled with the sizes of 380mm × 320mm × 10mm for this experiment.

TABLE I. CHEMICAL COMPOSITIONS OF 2219 ALUMINUM ALLOY (WT. %)

Cu	Si	Fe	Mn	Mg	V	Zr	Zn	Ti	Others	Al
5.8 - 6.8	≤ 0.2	≤ 0.3	0.2 - 0.4	≤ 0.02	0.05 - 0.15	0.1 - 0.25	≤ 0.1	0.02 - 0.1	≤ 0.15	Bal.

Figure I shows a two-robot cooperative experimental system, developed at Beijing University of Technology (BJUT). The welding robot with torch equipped with Tandem GMAW power source to implement WAAM, is RTI 2000 (IGM Robotersysteme AG, Wiener Neudorf, Austria). And the other robot mounted milling tool is KR500 (KUKA AG, Augsburg, Bavaria, Germany). The milling robot with a high-speed electric spindle ES779 (max. spindle speed is 22,000rpm) [11]. The standard cutting tool was applied by 3-flute solid carbide flat-end mill with a helix angle of 60° and a diameter of 10 mm axis.

FIGURE I. TWO-ROBOT COOPERATIVE PLATFORM OF HYBRID MANUFACTURE

To simulate thermally assisted machining environment of the plate work-piece, a heating system was mounted to the robot positioner which is displayed in Figure II.

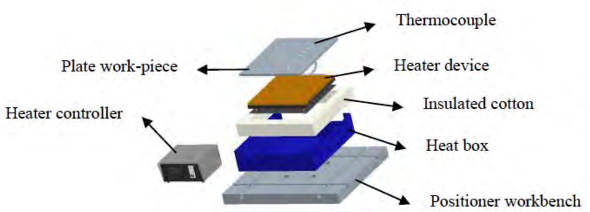

FIGURE II. EXPLODED-VIEW OF HEATING SYSTEM FOR THERMAL MACHINING

Using TR200 Surface Roughness Tester, the average surface roughness of the work-piece for the designed individual test for different condition.

B. *Experimental Design for Thermally Assisted Milling*

Machining parameters taken into account during machining in end milling process are spindle speed, feed rate and work-piece temperature. These three dependent variables are investigated using RSM. The center line average surface roughness named *R*a (arithmetic mean height).

The Central Composite Design (CCD) for RSM coded with five levels as -α, -1, 0, +1, +α. In order to improve prediction accuracy, rotatable design is used while a value of α is 1.682. 20 experiments are designed with the five levels and three-factor for estimation the pure error sum of squares at the central conditions. The selected cutting parameters and their ranges are feed per tooth, spindle speed and work-piece temperature. Table II presents the process variables and their range. There are 20 rows and 3 columns at five levels confirming to the experimental tests. Designed experiment runs and their predicted values of all responses are illustrated in Table III, including actual and coded. Feed per tooth (*fz*) is in the first column of the table, second column is spindle speed (*n*), work-piece temperature (*T*emp.) is in the third column.

TABLE II. PROCESS VARIABLES AND ITS BOUNDS

	Name	**Units**	**Low**	**High**	**-alpha**	**+alpha**
Factor A	*fz*	mm/s	0.0181	0.0419	0.01	0.05
Factor B	*n*	r/min	1006.75	2493.25	500	3000
Factor C	*Temp.*	℃	110.809	289.191	50	350
Response 1	*Ra*	μm	0.5693	2.5398		
Response 2	*Rz*	μm	3.2068	27.401		

TABLE III. CCD WITH OBSERVED AND PREDICTED RESPONSES

Std.	**Run**	***fz***	***n***	***Temp.***	**Ra**	**Rz**
14	1	1.5 (0)	1750.0 (0)	350.0 (+1.682)	1.192	6.664
18	2	1.5 (0)	1750.0 (0)	200.0 (0)	1.974	10.348
2	3	1.8 (+1)	1006.8 (-1)	110.8 (-1)	1.768	11.223
9	4	1.0 (-1.682)	1750.0 (0)	200.0 (0)	0.969	5.131
20	5	1.5 (0)	1750.0 (0)	200.0 (0)	2.074	10.545
1	6	1.2 (-1)	1006.8 (-1)	110.8 (-1)	2.014	10.287
10	7	2.0 (+1.682)	1750.0 (0)	200.0 (0)	1.217	6.711
5	8	1.2 (-1)	1006.8 (-1)	289.2 (+1)	1.255	6.885
19	9	1.5 (0)	1750.0 (0)	200.0 (0)	1.818	10.759
15	10	1.5 (0)	1750.0 (0)	200.0 (0)	1.287	7.246
6	11	1.8 (+1)	1006.8 (-1)	289.2 (+1)	2.017	13.422
13	12	1.5 (0)	1750.0 (0)	50.0 (-1.682)	1.248	7.878
4	13	1.8 (+1)	2493.3 (+1)	110.8 (-1)	0.938	4.930
8	14	1.8 (+1)	2493.3 (+1)	289.2 (+1)	1.510	27.401
12	15	1.5 (0)	3000.0 (+1.682)	200.0 (0)	1.371	9.651
11	16	1.5 (0)	500.0 (-1.682)	200.0 (0)	2.540	14.414
16	17	1.5 (0)	1750.0 (0)	200.0 (0)	2.133	10.258
7	18	1.2 (-1)	2493.3 (+1)	289.2 (+1)	0.569	3.207
17	19	1.5 (0)	1750.0 (0)	200.0 (0)	2.371	13.401
3	20	1.2 (-1)	2493.3 (+1)	110.8 (-1)	1.050	5.942

III. Results and Discussion

The analysis of variance (ANOVA) for deciding the parameters significantly of the experimental results is made by a software package Design Expert (Design Expert 8.0.7, 2010, Stat-Ease Inc., Minneapolis). The analysis is accomplished for a 95% confidence level or the significance level alpha (α) less than 0.05. Analysis of variance values are presented in Table IV. The model F-value of 5.23 implies the model is significant. There is only a 0.82% chance that a "Model F-value" this large could occur due to noise. The "Lack of Fit F-value" of 0.17 implies the Lack of Fit is not significant relative to the pure error. There is a 96.21% chance that a "Lack of Fit F-value" this large could occur due to noise. Non-significant lack of fit is good--we want the model to fit.

TABLE IV. ANALYSIS OF VARIANCE TABLE FOR RA

Source	**Sum of squares**	**df**	**Mean square**	**F-value**	**p-value**
Model	4.29	9	0.48	5.23	0.0082 Significant
A-feed	1.04	1	1.04	11.46	0.0069
B-speed	1.45	1	1.45	15.92	0.0026
C-temp.	0.075	1	0.075	0.82	*0.3855*
AB	0.083	1	0.083	0.91	*0.3634*
AC	0.30	1	0.30	3.34	*0.0977*
BC	1.278e-3	1	1.278e-3	0.014	*0.9081*
A^2	0.36	1	0.36	3.95	*0.0749*
B^2	2.164e-3	1	2.164e-3	0.024	*0.8806*
C^2	1.07	1	1.07	11.72	0.0065
Residual	0.91	10	0.091		
Lack of fit	0.13	5	0.027	0.17	*0.9621* Not significant
Pure error	0.78	5	0.16		
Cor total	5.20	19			

Cutting process is optimized based on the BBD developed in Design Expert Software of RSM. The average surface roughness Ra is checked on the base value of coefficient of regression (R^2), adjusted R^2, predicted R^2, coefficient of variation (C.V.), predicted residuals error sum of squares (PRESS), F-value and P-values (shown in Table V).

According to Joglekar and May [12] value of R^2 (Coefficient of regression) should be at least 0.80 for good fitting of a model. In this experiment, value of R^2 for Ra is 0.8247, which is lower than the satisfactory level and shows good adequacy of the model. Adequacy of precision measures the signal to noise ratio and ratio grater than 4 is desirable [13,14]. The "Pred R-Squared" of 0.5820 is in reasonable agreement in this study with the "Adj R-Squared" of 0.6669. The experimental ratio of 8.979 indicates an adequate signal, which is higher than 4. A good model will have a low PRESS value [15]. The sum of the squared named PRESS which is differences between the estimated and actual values over all the points. In this study, the PRESS value is 2.17, which does not show high value of PRESS indicating better fitting quality of the model. C.V. value expresses the variation in the actual and model predicted values. C.V. value of 18.50% in this study is still acceptable. According to the experimental data, the design space can be navigated by the values above.

TABLE V. RESULTS OF VARIANCE ANALYSIS OF RA

Std. Dev.	0.30	R-Squared	0.8247
Mean	1.63	Adj R-Squared	0.6669
C.V. %	18.50	Pred R-Squared	0.5820
PRESS	2.17	Adeq Precision	8.979

In current study, the relationship between the inputs named X (feed, speed and temperature of work-piece) and the outputs named Y, defines machinability of AA 2219 in terms of surface roughness. This relationship is given by Eq. (1).

$$Y = f(f, n, T) + e_{ij} \quad (1)$$

And Y is the desired machinability aspect and f_z is a function proposed by using a non-linear quadratic mathematical model, which is suitable for studying the interaction effects of process parameters on machinability characteristics. To make the comparison using ANOVA requires several assumptions to be satisfied. The assumptions underlying the analysis of variance tell the residuals are determined by evaluating Eq. (2).

$$e_{ij} = y_{ij} - \hat{y}_{ij} \quad (2)$$

Where e_{ij} is the residual, y_{ij} is the corresponding observation of the runs, and $\hat{y}_{ij}$ is the fitted value [16]. A check of the normally assumption is made by constructing the normal probability plot of the residuals, which is shown in Figure III. The structure less distribution of dots above and below the abscissa (fitted values) shows that the errors are independently distributed and the variance is constant [17].

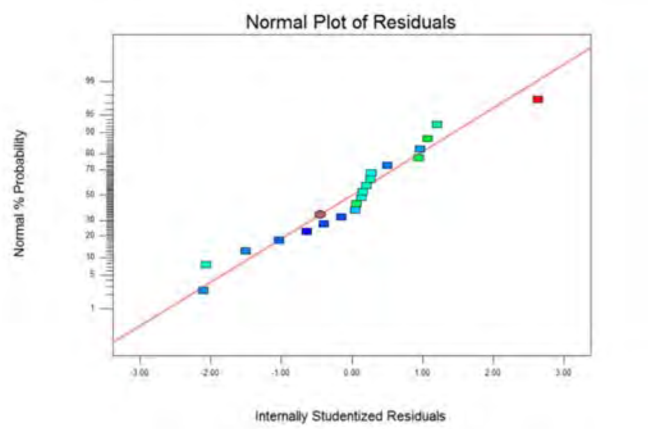

FIGURE III. NORMAL PLOT OF RESIDUALS FOR RA

In the present work, the relation between all responses and operating variables based second order mathematical model is given in Eq. (3).

$$Y = a_0 + \sum_{i=1}^{3} a_i X_i + \sum_{i=1}^{3} a_{ii} X_i^2 + \sum_{i=1}^{3} a_{ij} X_i X_j \quad (3)$$

Where a_0 is constant, a_i, a_{ii}, and a_{ij} represent the coefficients of linear, quadratic and cross product terms, respectively. X_i reveals the coded variables that correspond to the studied machining parameters [18].

The surface roughness (Ra) model is given below in Eq. (4), which is in terms of actual factors.

$$\begin{aligned} Ra = 1.51 + 32.54 f_z - (7.41\times10^{-4})\cdot n \\ + (7.06\times10^{-3})\cdot T + 0.01 f_z \cdot n \\ + 0.18 f_z \cdot T + (1.91\times10^{-7}) n \cdot T \\ - 1098.0 f_z{}^2 - (2.22\times10^{-8}) n^2 \\ - (3.42\times10^{-5}) T^2 \end{aligned} \tag{4}$$

From analysis of variance in Table IV, some parameters are not significant. Eq. (4) can be simplified to Eq. (5).

$$\begin{aligned} Ra = 1.51 + 32.54 f_z - (7.41\times10^{-4})\cdot n \\ - (3.42\times10^{-5})\cdot T^2 \end{aligned} \tag{5}$$

The surface plots of 3D model are provided with two factors at the same time. These fixed levels of the response factors provide the interaction information effects the two input factors, which helps to optimize level for each variable to obtain the maximum response [19].

IV. CONCLUSIONS

This work proposed a multi-objective solution for the minimization of surface roughness in a hybrid manufacturing process combining WAAM and milling. Cutting process parameters of this thermally assisted milling in hybrid process were optimized including feed per tooth, spindle speed and temperature of work-piece. Using the response surface methodology, the experiments are designed in five levels for the milling of AA2219. Based on the experimental data above, the following conclusions were made:

1) The mathematical model provides good co-relation between the responses and the process parameters developed in the work. The predicated model of surface roughness indicates that the temperature is a significant parameter in thermal cutting.

2) The mathematical models of surface roughness in different temperature are well-fitted and the estimated values of the responses are closer to the investigation's results with 95% confidence level.

3) Experiments show that higher spindle speed and lower feed rate can achieve a satisfactory surface roughness. It is observed that the surface roughness increases firstly and then decreases with the temperature of the work-piece which can reach the finished or semi-finish machining level.

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