Predictive Manufacturing: Subtractive and Additive

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Abstract: Manufacturing is the key to today’s industrial competitiveness, and it is broadly classified into two categories, subtractive and additive. In current study, the ability to predictively model manufacturing performance attributes in both categories is introduced. In subtractive manufacturing, modeling of laser-assisted and ultrasonic vibration-assisted milling are presented. In laser-assisted milling, the laser preheating temperature field is predicted, and the dynamic recrystallization as well as grain growth triggered under high temperature is considered, which enhances the accuracy of force and residual stress prediction. In ultrasonic vibration-assisted milling, the intermittent effect is considered through tool-workpiece separation criteria. And the force reduction in ultrasonic vibration-assisted milling is accurately predicted. In additive manufacturing, laser-assisted metal additive manufacturing is introduced. And the predictive modeling of temperature field in powder bed metal additive manufacturing is presented. The model considers heat transfer boundary including heat loss from convection and radiation at the part boundary. Through the comparison between measured and calculated molten pool dimensions, the model is proven to have high computational efficiency and high prediction accuracy.

1. Introduction

1.1. Subtractive manufacturing
In subtractive manufacturing, advanced machining technologies have been developed for years in order to obtain higher material removal rate, better surface finish, and better fatigue resistance, while keeping tool wear rate and cutting force at a low level. In addition, the use of these technologies could enhance the machinability of some difficult-to-machine materials such as Inconel 718 and Ti6Al4V, which typically have high strength and cause large cutting forces, high cutting temperature, severe tool wear, and bad surface finish in conventional machining process. Laser-assisted and ultrasonic vibration-assisted milling are two of the advanced technologies applied in subtractive manufacturing. The former reduces cutting force by softening the workpiece through laser preheating, while the latter has the same effect through discontinuous machining process under ultrasonic vibration of the tool. However, with the use of advanced technologies such as laser and ultrasonic vibration, more challenges appear for the process control. For example, under high cutting speed, the use of laser could lead to higher flank wear or even tool breakage [0] comparing with conventional milling, when inappropriate combination of cutting and laser parameters are used. The ultrasonic vibration could also speed up the tool wear rate and further lead to larger surface roughness than conventional milling [0]. Therefore, predictive modeling is important to calculate force, temperature, residual stress, tool wear, and surface roughness in laser-assisted and ultrasonic vibration-assisted milling process. Several predictive models have been proposed so far. Pan et al. [0] predicted force in laser-assisted milling of Inconel 718. The oblique cutting is transferred to equivalent orthogonal cutting at each
rotation angle. Then based on mechanics of machining, the forces in cutting and radial directions are calculated. The axial force is calculated according to tool geometry. However, the preheating temperature is calculated through numerical simulation, and the microstructure evolution is not considered. Tian et al. [0] proposed thermal modeling of laser-assisted milling to predict temperature field by determining spatial distribution of the laser energy and heat transfer equations including conduction, convection, and radiation. Although good agreement was found, the validation heating tests were conducted without material removal. Therefore, only the laser preheating temperature was predicted without machining induced temperature rise. Ulutan et al. [0] proposed an analytical model for residual stress, in which the thermal and mechanical loading were computed through elastic-plastic model and relaxation process. Huang et al. [0-0] proposed the tool wear prediction model in hard turning of Cubic Boron Nitride cutters, which considered abrasion, adhesion, and diffusion. These models are only in orthogonal cutting or turning process without laser effect. Hao et al. [0] developed surface roughness prediction model of ball end milling cutter. The geometrical model of the tool was built by considering tool path, cutting edge, and tool axis. The model was then corrected under the deformation caused by milling force. But the response of workpiece was not included. Verma et al. [0] predicted static machining force in axial ultrasonic vibration-assisted milling. The instantaneous chip thickness is calculated based on the frequency and maximum velocity of vibration, and the mean cutting force for the specific tool angular position is derived from contact ratio and shear flow stress based on Johnson–Cook model. This method is able to calculate mean oblique cutting forces accurately through mechanics of machining. However, the tool-workpiece separation criterion in axial direction is relatively easy to decide, and the dynamics of moving tool or workpiece is simplified as a contact ratio. Khajehzadeh et al. [0] proposed theoretical model of tool temperature in ultrasonic vibration-assisted turning. The tool position is the superposition of linear feed movement and sinusoid vibration movement. The primary heat source in shear zone and secondary heat source at tool-chip interface are considered. However, the rubbing heat source on tool-workpiece interface is ignored. Gao and Sun [0] did analytical predictive modeling of surface roughness for two-dimensional vibration-assisted machining based on kinematics and tool geometry analysis, but the effects of forces and workpiece recovery are ignored. The residual stress and tool wear models have not been proposed in ultrasonic vibration-assisted milling.

1.2. Additive manufacturing

Laser-assisted metal additive manufacturing (LMAM) can produce geometrically complex parts with effective cost [0]. High-density laser power is employed to fully melt or fuse metal powders to build parts in a layer-by-layer manner. The LMAM processes can be broadly classified into two categories, namely powder bed metal additive manufacturing (PBMAM) and powder feed metal additive manufacturing (PFMAM). However, defects such as crack, porosity, undesired residual stress, and distortion are frequently observed in the parts produced by the LMAM process [0-0]. The large thermal gradient, due to the repeatedly rapid heat and solidification during the process, causes those common defects, as reported in the literature [0,0]. Different methods have been employed for temperature investigation. They are experimental technique, numerical modeling, and analytical modeling. Experimental techniques include in-situ measurement and post-process measurement were employed for temperature investigation. The in-situ measurement techniques such as embedded thermocouple and infrared camera are widely used for temperature measurement in different manufacturing processes [0-0], which cannot achieve three-dimensional temperature measurement inside the build in LMAM processes [0,0]. The post-process measurement technique based on solidification microstructure measured under microscope required extensive experimental work for sample preparation [0]. The experimental techniques are limited by the restricted accessibility under elevated temperature levels. Numerical models were developed based on the finite element method (FEM), which were computationally expensive. Roberts et al. developed a FEM model to predict the temperature distribution in multi-track, multi-layer scans using element birth and death technique [0]. Fu et al. developed another FEM model to predict the temperatures using solid material properties and powder material properties [0]. Similar models were employed for different LMAM processes with various materials [0]. Xia et al. developed a FEM model taking powder packing and powder size variation into
consideration, which allows the prediction of build porosity [0]. FEM models were also employed for the prediction of residual stress and part distortion [0,0]. Although numerical models have made considerable progress on the prediction of the LMAM process, the expensive computational cost is still a major drawback.

Analytical models were developed based on the physics and heat transfer mechanism. Analytical models can calculate the three-dimensional temperature distribution in LMAM without resorting to FEM or any iteration-based simulations, and thus has promising short computational time. Van Elsen et al. summarized three moving heat source solutions, namely, point moving heat source solution, semi-ellipsoid moving heat source, and uniform moving heat source respectively [0]. The assumptions of the semi-infinite workpiece, and isotropic and homogeneous material were enforced in those models. The point moving heat source solutions was originally proposed by Carslaw and Jaeger [0]. Ning et al. further developed the point moving heat source to predict the temperature in multi-track scans considering the scanning strategy. The molten pool evolution was also calculated with temperature prediction [0]. Cline et al. developed another analytical model assuming a moving hear source with Gaussian distributed intensity profile [0]. This solution became the point moving heat source solution by reducing the beam radius to zero. Rosenthal developed a line moving heat source solution for welding process [0]. The semi-infinite medium was assumed in this solution. However, the developed analytical models cannot handle the heat transfer boundary condition, which resulted in unoptimized prediction accuracy, and thus prevent the accurate prediction for porosity, residual stress, and part distortion. The semi-analytical model was developed for temperature prediction, in which FEM was employed for imposing heat transfer boundary conditions [0]. The involvemnt of FEM unavoidably compromises the computational efficiency. In addition, Green’s function was suggested by Carslaw and Jaeger for temperature prediction in a bounded medium. However, the complex mathematical calculations unavoidily reduce computational efficiency. To the knowledge of authors, a computationally efficient analytical model considering heat transfer boundary condition is not available yet.

2. Predictive modeling in subtractive manufacturing

The flow chart of the proposed predictive model is shown in Figure 1. Asterisk indicates step only in laser-assisted milling, while double asterisk indicates step only in ultrasonic vibration-assisted milling. At each rotation angle of milling tool, the cutting parameters and tool geometry parameters are recalculated as in equivalent orthogonal cutting. Then, the milling forces are calculated through flow stress based on mechanics of machining [0,0]. The forces also result in heat sources in machining temperature prediction [0]. And the residual stress is predicted based on mechanical stress from force and thermal stress from temperature field, followed by relaxation process [0-0]. The surface roughness is calculated considering the tool deformation under forces, tool path, and the elastic recovery of machined surface [0,0]. Lastly, the tool flank wear rate is decided by abrasive, adhesive, and diffusive wear based on the stress and temperature on tool-workpiece interface [0,0]. For laser-assisted milling, the laser preheating temperature field is predicted which affects the flow stress and overall temperature field [0]. In addition, the high temperature could trigger the microstructure evolution, which leads to grain growth and change of flow stress. For ultrasonic vibration-assisted milling, tool-workpiece separation criteria are examined first, and the prediction is only continued when there is contact between tool and workpiece at the moment [0].
2.1. Laser-assisted milling

The laser preheating temperature increase rate at top surface is described by

$$\Delta T_{laser}(x,0) = \frac{q(x) - h(T_{laser}(x,0) - T_0)}{\rho c_p}$$

(1)

where $T_{laser}$ is the laser preheating temperature, $\rho$ is the material density, $c_p$ is specific heat, $h$ is the heat transfer coefficient, $T_0$ is the environment temperature, $q(x)$ is the heat generation rate due to laser power described by the Gaussian equation as

$$q(x) = \frac{2Q}{\pi r^2} \exp(-\frac{2x^2}{r^2})$$

(2)

where $Q$ is the total input power of laser, $r$ is the radius of laser spot. Within the workpiece, heat conduction is the dominant effect with the governing equation of

$$\Delta T_{laser}(x,z) = \alpha V_f \frac{\partial T_{laser}(x,z)}{\partial x}$$

(3)

where $\alpha$ is thermal diffusivity and $V_f$ is the moving speed of laser spot or the feed speed. The first term on the right describes the two-dimensional heat conduction, while the second term considers the effect of moving laser beam in cutting direction.

The recrystallization effect is considered through modified Johnson-Cook flow stress model as

$$\sigma = (A_0 + K_0 d^{0.5}) + B\bar{\varepsilon}^{\gamma})(1 + C \ln \frac{\dot{\varepsilon}}{\dot{\varepsilon}_0})\left\{1 - \left(\frac{T - T_0}{T_m - T_0}\right)^n\right\}$$

(4)
where $A_{hp}$, $K_{hp}$, $B$, $C$, $m$ and $n$ are material constants, $\varepsilon$ is the plastic strain, $\dot{\varepsilon}$ is the plastic strain rate, $\dot{\varepsilon}_0$ is the reference strain rate, and $T_m$ is the melting temperature. The average grain size $d$ is

$$d = d_{drex}X_{drex} + d_0(1 - X_{drex})$$  \hspace{1cm} (5)

where $d_0$ is the initial average grain size, $d_{drex}$ is the dynamically recrystallized average grain size and $X_{drex}$ is the recrystallized volume fraction.

As shown in Figure 2, with the consideration of microstructure evolution and grain growth, the error between measurements and predictions is less than 20% during laser-assisted milling of Inconel 718. As shown in Figure 3, good agreement is found between measurements and predictions for residual stress after laser-assisted milling of Ti6Al4V. And the residual stress profile moves toward less compressive direction due to thermal softening effect.

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2.2. Ultrasonic vibration-assisted milling

Kinematic analysis is conducted to check the tool-workpiece separation criteria. The velocity of tool tip is described by

$$V_x(t) = \omega A_x \cos(\omega t) - f \cos(\phi_x) ; \quad V_y(t) = \omega A_y \cos(\omega t) + V_y \sin(\phi_y)$$  \hspace{1cm} (6)

where $V_t$ is the cutting speed dependent on spindle rotation frequency and cutter size, $\phi_x$ is rotation angle, $f$ is the feed rate, $\omega = 2\pi f_0$, $f_0$ is the ultrasonic vibration frequency, $A_x$ and $A_y$ are the vibration amplitude in each direction. There is no contact if the cutting direction component of the relative velocity between tool and workpiece is opposite to the tool rotation direction [0,0]. As shown in Figure 4(a),
is the resultant cutting velocity based on Equation (6), while \( V_{ul} = z'(t) \) is the ultrasonic vibration velocity in axial direction, \( \beta \) is the helix angle. In Figure 4(b), the component along the transverse direction decides the intermittent effect at it is perpendicular to the uncut surface. When this component is negative, which is opposite to the tool rotation direction, there is no contact between tool and workpiece as described by

\[
V_n \cos(\beta) - V_{ul} \sin(\beta) < 0
\]  

Figure 4. Velocity at the tool tip due to tool rotation and ultrasonic vibration: (a) representation of \( V_n \) and \( V_{ul} \) at the cutting tip (b) resolved component at the tip.

According to the average cutting forces from experiments and predictive model on Aluminum alloy 2A12 as shown in Figure 5, the average values decrease by 39% in feed direction and 35% in cutting direction when the ultrasonic vibration is applied. In addition, the measured forces keep dropping gradually when the amplitude increases, since the tool-workpiece separation time is longer under higher vibration amplitude. Overall, the proposed force prediction model is able to match the trend with average error of 13.6% in \( F_x \) and 13.8% in \( F_y \).

3. Predictive modeling in additive manufacturing

3.1. Methodology
Ning et al. presented an analytical model for temperature prediction in metal additive manufacturing with consideration of heat transfer boundary [0, 0]. The heat transfer mechanism in PBMAM is illustrated as in Figure 6, in which the red arrow and green arrows denote the heat input from the laser, and heat loss from convection and radiation at the part boundary respectively. The build porosity,
residual stress, and distortion can be predicted based on the temperature investigation, which are discussed as future works.

\[ \theta_{\text{laser}}(x, y, z) = \frac{P \eta}{4 \pi k R(T_m - T_0)} \exp \left( -\frac{V(R+x)}{2k} \right) \]  

where \( P \) is laser powder, \( \eta \) is absorption, \( V \) is heat source moving velocity along \( x \) the direction, \( k \) is thermal diffusivity, \( \kappa = k/\rho c \), where \( k, \rho, c \) are thermal conductivity, density, and specific heat respectively, \( R \) is the distance from laser heat source \( (R = x^2 + y^2 + z^2) \), \( x, y, z \) are the corresponding distances from the laser source respectively, \( \theta \) is dimensionless temperature \( (\theta = (T - T_0)/(T_m - T_0)) \), \( T_m, T_0 \) are the material melting temperature and room temperature respectively.

The heat sink solution was derived with an equivalent power for heat loss from convection and radiation, and zero moving velocity. The convection and radiation can be calculated as

\[ Q_{\text{conv}} = Ah(T - T_0) \quad Q_{\text{rad}} = A\varepsilon \sigma(T^4 - T_0^4) \]  

where \( Q_{\text{conv}} \) and \( Q_{\text{rad}} \) denote heat loss due to convection and radiation respectively, \( A \) is the area of heat sink, \( h \) is convection coefficient, \( \varepsilon \) is emissivity, \( \sigma \) is Stefan-Boltzmann constant, \( T \) is the temperature of the heat sink that can be estimated by the point moving heat source solution, \( T_0 \) is room temperature.

The equivalent power for heat loss at the part boundary can be expressed as

\[ P_{\text{equiv}} = Ah(T - T_0) + A\varepsilon \sigma(T^4 - T_0^4) \]  

The part boundary is mathematically discretized into many sections (heat sinks) considering the non-uniform temperature distribution at the part boundary, which causes non-uniform heat loss at the boundary.

\[ \theta_{\text{loss}}(x, y, z) = \sum_{i=0}^{n} A_i \frac{h(T_i - T_0) + \varepsilon \sigma(T_i^4 - T_0^4)}{4\pi \kappa R(T_m - T_0)} \]  

where \( n \) is the number of heat sinks, \( i \) is the index of each heat sink.

The final temperature solution is constructed from the superposition of heat source solution and heat sink solutions as the following

\[ \theta_{\text{laser}}(x, y, z) = \frac{P \eta}{4 \pi k R(T_m - T_0)} \exp \left( -\frac{V(R+x)}{2k} \right) - \sum_{i=0}^{n} \frac{h(T_i - T_0) + \varepsilon \sigma(T_i^4 - T_0^4)}{4\pi \kappa R(T_m - T_0)} \]  

In addition, the latent heat \((L_f)\) was considered using heat integration method [0], in which the temperature were lowered because of phase transformation with continuous heat input.

\[ \Delta T = \frac{L_f}{c} \]
3.2. Results and discussion
The temperature profiles were calculated by the presented model in PBMAM of Ti6Al4V. The thermal physics properties of Ti6Al4V are given in Table 1. It should be noted that the temperature-dependent material properties used only for the investigation of material properties variation. A 6 by 6 heat sink setting were determined based on the calibration with experimental measurement of the molten pool under test 1 process condition.

| Name                        | Symbol | Value                          | Unit         |
|-----------------------------|--------|--------------------------------|--------------|
| Density                     | μ      | 4428                           | kg/m³        |
| Thermal conductivity        | k_p    | 6.6                            | W/(m·K)      |
| (powder at T₀)              |        |                                |              |
|                             |        | \(-0.797 + 18.2 \times 10^{-3}T\) |              |
|                             |        | \(-2 \times 10^{-6}T^2\)       |              |
| Thermal conductivity        | k_s    | 33.4                           | W/(m·K)      |
| (solid)                     |        | T<1923K                        |              |
|                             |        | 33.4                           |              |
|                             |        | T>1923K                        |              |
| Specific heat (powder at    | c_p    | 580                            | J/(kg·K)     |
| T₀)                         |        |                                |              |
|                             |        | \(411.5 + 2 \times 10^{-2}T - 5 \times 10^{-7}T^2\) | |
| Specific heat (solid)       | c_s    | 830                            | J/(kg·K)     |
|                             |        | T<1923K                        |              |
|                             |        | 830                            |              |
|                             |        | T>1923K                        |              |
| Latent heat                 | H_f    | 365000                         | J/kg         |
| Room temperature            | T₀     | 20                             | °C           |
| Solidus temperature         | T_s    | 1605                           | °C           |
| Liquidus temperature        | T_l    | 1655                           | °C           |
| Heat convection coefficient | h      | 24                             | W/(m²·K)     |
| Emissivity                  | ε      | 0.9                            | 1            |
| Stefan-Boltzmann constant   | σ      | 5.67 10-8                      | W/(m²·K⁴)    |
| Absorption                  | η      | 0.77                           | 1            |

Note: the temperature-sensitive material properties are only used for the investigation of material property variation.

The three-dimensional temperature profile was illustrated in Figure 7, in which the temperature profiles (solid lines) were compared to those calculated without considering heat loss (dashed lines). The temperature affected material property variations were shown in Figure 8, a) for thermal conductivity, b) for specific heat. The molten pool dimensions were determined by comparing the calculated temperature with the materials melting temperature. The molten pool dimensions were calculated under different process conditions and validated to the documented experimental values based on the solidification microstructure. As shown in Table 2, close agreements were observed upon validation to the experimental values. The computational time using a personal computer was recorded and presented.
Figure 7. Calculated temperature profiles under test 1 process condition. Red circles denote the centers of heat sinks. For comparison, the temperature profiles (dashed lines) were calculated without the consideration of heat transfer boundary condition. The temperature profiles (solid lines) were calculated with consideration of heat loss from convection and radiation at the part boundary.

Figure 8. Calculated temperature-affected material properties (a) thermal conductivity (b) specific heat.

Table 2. Process conditions, experimental molten pool dimensions, calculated molten pool dimensions [0].

| Test | Power (W) | Scanning Velocity (mm/s) | Molten pool width (μm) | Molten pool depth (μm) | Molten pool length* (μm) | Molten pool width* (μm) | Molten pool depth* (μm) | Computation time* (s) |
|------|-----------|--------------------------|------------------------|------------------------|--------------------------|------------------------|------------------------|------------------------|
| 1    | 100       | 500                      | 118                    | 62                     | 530                      | 120                    | 63                     | 93.73                  |
| 2    | 100       | 750                      | 98                     | 52                     | 537.5                    | 100                    | 50                     | 88.52                  |
| 3    | 100       | 1000                     | 75                     | 31                     | 537.5                    | 90                     | 45                     | 88.35                  |
| 4    | 100       | 1200                     | 72                     | 36                     | 537.5                    | 80                     | 40                     | 88.74                  |
| 5    | 150       | 500                      | 146                    | 122                    | 752.5                    | 145                    | 113                    | 90.33                  |
| 6    | 150       | 750                      | 136                    | 88                     | 787.5                    | 125                    | 83                     | 91.10                  |
| 7    | 150       | 1000                     | 116                    | 85                     | 797.5                    | 110                    | 85                     | 91.02                  |
| 8    | 150       | 1200                     | 108                    | 59                     | 800                      | 100                    | 60                     | 89.76                  |

Note: * denotes the calculated values using the presented model.
With the benefits of high computational efficiency and high prediction accuracy, the presented model can be used for temperature investigation for larger parts and process-parameters planning through inverse analysis [0-0]. Future works can be made to improve the presented model for powder feed metal additive manufacturing. The powder size distribution and powder packing should be considered because of their influence on material thermophysical properties.

Build porosity, residual stress and part distortion can be predicted based on the calculated temperatures as future works as illustrated in Figure 9. Some preliminary works on the predictions of build porosity and residual stress can be found in the references [0, 0]. The thermal stress was predicted by the thermoelasticity theory from the calculated temperatures. The residual stress was calculated by the elastoplastic contact algorithm and relaxation procedures. The build porosity can be predicted through regression analysis based on available experimental data.

![Figure 9. Flowchart of the predictive models in metal additive manufacturing including the presented model and future works.](image)

4. Summary

In subtractive manufacturing, predictive modeling of laser-assisted and ultrasonic vibration-assisted milling is introduced. The effects of laser preheating and grain growth are considered in laser-assisted milling, while the intermittent tool-workpiece separation is considered in ultrasonic vibration-assisted milling. The preheating temperature field is predicted by considering the heat generation from laser and convection. The heat generation rate is described by Gaussian equation. The Hall-Petch equation is used to define a modified Johnson-Cook model parameter and account for grain growth effect. The tool-workpiece separation criterion is checked based on the instantaneous position and velocity of tool. Good agreements were found between measurements and predictions of force and residual stress in laser-assisted milling. And the force reduction in ultrasonic vibration-assisted milling was also accurately predicted.

In additive manufacturing, a closed-form solution was presented for temperature prediction in PBMAM configuration, without resorting to mesh of any iteration-based simulations. The temperature increase from the laser heat source and temperature decrease from the heat loss at the part boundary were calculated using point moving heat source solution and heat sink solutions respectively. The molten pool dimensions were calculated from the predicted temperature profile. Good agreements were observed upon validation to the documented experimental measurements. The high prediction accuracy allows the temperature prediction for large-scale parts and process-parameters planning through inverse
analysis. The build porosity, residual stress, and part distortion can be further investigated based on the temperature investigation.

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