Material removal and wheel wear models for robotic grinding wheel profiling

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Abstract

In hydro turbine manufacturing and repair, grinding of certain high-curvature surfaces like fillet welds presently cannot be carried out by robots so hand grinding is necessary. During this process, the grinding wheel is moved back and forth over the workpiece and thus the wheel maintains its profile and better control of the material removal rate is achieved. To automate such a process, material removal and wheel wear models must be developed and experimentally validated under specific operating conditions. This paper presents the study of predictive models to support automation of grinding wheel profiling.

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Nomenclature

\[ \begin{align*}
C & \quad \text{experimental coefficient} \\
\epsilon_n & \quad \text{experimental coefficient} \\
F_n & \quad \text{normal force (N)} \\
F_{n0} & \quad \text{threshold normal force (N)} \\
K_n & \quad \text{experimental coefficient} \\
P & \quad \text{grinding power (W)} \\
R_{eq} & \quad \text{equivalent profile radius (m)} \\
v_f & \quad \text{feed velocity (m/s)} \\
v_t & \quad \text{tangential velocity at the point of contact (m/s)} \\
Z_s & \quad \text{wheel wear rate (m³/s)} \\
Z_w & \quad \text{material removal rate (m³/s)} \\
\beta & \quad \text{frontal angle (rad)} \\
A_w & \quad \text{material removal parameter (m³·N⁻¹·s⁻¹)} \\
\omega & \quad \text{rotation speed (RPM)} 
\end{align*} \]

1. Introduction

SCOMPI is a portable robot developed at Hydro-Québec’s research institute, IREQ, for hydro turbine manufacturing and repair. With this multi-process robot, welding, grinding, polishing and similar processes can be automated [1][2]. Certain high-curvature surfaces, however, cannot presently be carried out by the robot so hand grinding is necessary. Plug wheels used for this type of application have the drawback of wearing down very quickly, complicating the control of robot orientation and position during the process. During hand grinding, the operator intuitively moves the tool back and forth, maintaining the wheel profile, helping grain self-sharpening and improving control of material removal from the workpiece. It is this wheel profiling process that sets constraints to robotic grinding of certain surfaces. To extend the application of SCOMPI, this paper presents the study of material removal and wheel wear models under specific conditions of grinding wheel profiling. This study identifies the variables that significantly improve predictive models.

Fig. 1. SCOMPI equipped with a custom grinder for hard-to-reach locations and a plug wheel.
2. Grinding wheel profiling

Grinding wheel profiling consists in moving the wheel back and forth over the workpiece in order to control wheel wear and better control material removal from the workpiece. For robotic or manual applications, resin-bonded wheels are used. Unlike vitrified wheels used in conventional grinding, resin-bonded wheels are resilient and thus better resist impacts [3]. Properly used, such wheels can wear down completely without glazing and with no need for dressing. Note that since the uncut chip (area of contact) moves across the wheel profile during the profiling process, variation in the effective radius of grinding must be considered. It was thus possible to optimize the efficiency of the hybrid force-position loop for grinding power control [4]. Tests were performed varying the grinding parameters: grinding power $P$, feed velocity $v_f$, rotation speed $\omega$ and frontal angle $\beta$. Grinding power and normal force were measured during grinding. Material removal and wheel wear were measured before and after grinding. The tangential velocity at the point of contact $v_t$ and equivalent profile radius $R_{eq}$ were used to develop and validate the models.

3. Material removal model

Test results showed that the normal force and grinding power combined increased the correlation by nearly 22% compared to linear regression using power alone (Fig. 2).

![Fig. 2. Variable-power tests: material removal rate as a function of normal force and power.](image)

In Fig. 3, data from tests at varying feed velocities and rotation speeds was plotted over that from the variable-power tests (black dots). Fig. 3a shows that no significant variation in material removal rate occurs when feed velocity and rotation speed vary. As Fig. 3b shows, this stable material removal rate results from a greater depth of cut when the feed velocity is low and a lesser depth of cut when the feed velocity is high. Furthermore, the depth of cut remains stable when the rotation speed $\omega$ changes from 18000 to 16000 RPM.
The material removal models from Hahn and Lindsay [5] (Eq. (1)) and from Kurfess et al. [6] (Eq. (2)), as well as a number of empirical models (Eq. (3), (4) and (5)) were tested. The latter models, based on the empirical formulation of Tönshoff et al. [7], ignore the velocity of the wheel relative to the workpiece at the point of contact. Since cut kinematics differ in robotic and conventional grinding, the tangential velocity at the point of contact $v_t$ and the wheel feed velocity $v_f$ are represented individually in the empirical models.

Table 1 gives the adjusted correlation coefficients from the material removal models for all tests performed. Model robustness under diverse conditions of use can be gauged using this approach. All cases can be analyzed either instantaneously (measurements throughout the grinding passes) or by averaging (mean of parameters per pass).

First, it is interesting to note that models considering the normal force but not grinding power (Eq. (1) and (4)) have a correlation coefficient of nearly zero for instantaneous measurements and of zero when averaged per pass. Such results are unsurprising for Eq. (1) since the material removal parameter $A_0$ and threshold normal force $F_{n0}$ are known to be affected by the variation of other process parameters [8]. Normal force is thus not a variable that alone suffices to predict material removal during the profiling operation. In general, the other models achieve a better correlation when the data is averaged over the grinding pass.

The model from Kurfess et al. (Eq. (2)) shows that grinding power alone can explain more than 40% of instantaneous material removal and nearly 55% of average material removal. With the empirical model in Eq. (3), which also uses grinding power, slightly higher correlations are achieved.
By combining normal force and grinding power in the empirical model in Eq. (5), a correlation of 71% is achieved for instantaneous measurements and of more than 83% for averages. By adding normal force to the empirical power model (Eq. (3)), it is thus possible to improve the model's correlation significantly: by nearly 73% for instantaneous measurements and by 52% for averages. These two parameters combined explain the major part of the variation in material removal.

4. Wheel wear model

Since the volume of wheel wear is only measured after each pass, wheel wear models are always analyzed based on the average value of the parameters per grinding pass. Furthermore, since wheel wear is very sensitive to variations in parameters, analyses were always conducted on variable-power tests with feed velocity and rotation speed held constant.

For manual grinding processes, such as deburring and cutting, Malkin and Guo [9] propose that the wheel wear rate be estimated based on an exponential relation to the material removal rate (Eq. (6)). Again based on the empirical formulation of Tönshoff et al. [7], other models were studied (Eq. (7), (8) and (9)). To plan oscillation in a grinding task, the oscillation model developed in this study [10] requires a wear model relating material removal rate to wheel wear rate. This is why Eq. (10) provides an empirical model that predicts wheel wear by combining all parameters controlled during the process with the material removal rate.

Table 2 presents the correlation coefficients for wheel wear models. It is interesting to note that coefficient $K_2$ in Eq. (6) is 1.020. For all practical purposes under normal conditions of use, this model thus provides a proportional relationship linking wheel wear rate to material removal rate. With a correlation exceeding 30%, this model performs better than the empirical models in Eq. (7) and (8). No correlation is achieved when a model considers the normal force but ignores grinding power (Eq. (8)). Though the correlation coefficient remains very low, Eq. (9) achieves the best correlation by combining normal force measurements and grinding power to predict wheel wear. Of all the variables considered in the empirical model in Eq. (10), only the tangential velocity at the point of contact $v_t$ and the material removal rate $Z_w$ proved to be significant variables in explaining wheel wear. It is also noteworthy that $v_t$ was identified as a significant variable in all models in which it was used. Moreover, the coefficient $e_1$ assigned to that variable in the models was always negative, explaining the quicker wheel wear when grinding on the tip of the wheel.

Table 2. Correlation coefficients for wheel wear models.

| Wheel wear model | Equation | $R^2_{adj}$  |
|------------------|----------|--------------|
| $Z_w = K_2Z_w^{2}$ | (6) | 0.307 |
| $Z_w = C_1v_t^2v_f^2P^eR_{eq}^{-e}$ | (7) | 0.287 |
| $Z_w = C_2v_t^2v_f^2F_n^{-e}P_{eq}^{e}$ | (8) | 0.000 |
| $Z_w = C_3v_t^2v_f^2P_{eq}^{-e}R_{eq}^{e}$ | (9) | 0.457 |
| $Z_w = CZ_w^{e}v_t^2v_f^2P_{eq}^{-e}R_{eq}^{e}$ | (10) | 0.440 |

Note that a broader study was conducted on the effect all of the parameters measured during the process ($Z_w$, $v_f$, $v_t$, $F_n$, $P$, $R_{eq}$ and $\beta$) have on predicting wheel wear. With multiple second-order polynomial regressions, that study added interaction terms between explanatory variables involving the product of the parameters. The models obtained were very complex and did not significantly improve the correlation of the wheel wear models.

The self-sharpening nature of the wheel makes abrasive machining more complex since various modes of grit wear exist [11]. Such factors as the magnitude of vibrations during manual or robotic grinding can also accelerate wear [12]. All of these factors explain the low correlation from wear models.
5. Conclusion

A number of predictive models were tested in order to control wear of the wheel profile and to better control material removal from the workpiece during robotic grinding. Test results showed the importance of combining normal force and grinding power in order to increase significantly the robustness of material removal models. The study also demonstrated that it is more difficult to predict wheel wear than material removal. However, the tangential velocity at the point of contact proved to be a significant variable in all wear models studied. This observation is particularly pertinent in profiling since the tangential velocity at the point of contact varies constantly due to wheel oscillation over the workpiece. Further research on wheel wear is needed to identify other parameters and relationships in order to better predict changes to the wheel profile.

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