Available online at www.sciencedirect.com

ScienceDirect

Procedia CIRP 77 (2018) 90–93

www.elsevier.com/locate/procedia

8th CIRP Conference on High Performance Cutting (HPC 2018)

Probabilistic Prediction of Cutting and Ploughing Forces using Extended Kienzle Force Model in Orthogonal Turning Process

M. Salehi[a,c]*, T.L. Schmitz[b], R. Copenhaver[b], R. Haas[c], J. Ovtcharova[a]

[a]*Institute for Information Management in Engineering, Karlsruhe Institute of Technology, Kaiserstr. 12, 76131, Karlsruhe, Germany*
[b]*Department of Mechanical Engineering and Engineering Science, University of North Carolina at Charlotte, Charlotte, NC, USA*
[c]*Institute of Materials and Processes, Karlsruhe University of Applied Science, Moltkestr.30, 76133, Karlsruhe,Germany*

* Corresponding author. Tel.: +49-721-925-2087; fax +49-721-925-2024. *E-mail address:* mehdi.salehi@hs-karlsruhe.de

Abstract

Probabilistic prediction of cutting and ploughing forces is performed by applying Bayesian inference to an extended Kienzle force model. Prior probabilities are established and posterior force predictions are completed. The results of the probabilistic force predictions are then verified using forces measured under other cutting conditions, as well as a simplified slip-line force model. Additionally, probabilistic simulation results are compared with the results of a non-linear least squares fitting technique to isolate the shearing and ploughing force components of the cutting force.

Keywords: Cutting force; Kienzle model; Ploughing force; Bayesian inference; MCMC

1 Introduction

Machining process models describe relationships between the input variables (i.e., feed, cutting speed, and cutting tool geometry) and the outputs, such as tool life and cutting force. In this context, several models have been developed to predict the cutting force [1]. The semi-empirical Kienzle force model describes a nonlinear relationship between the uncut chip thickness and cutting force using a power law [2]. The model predicts the force value deterministically and, therefore, the process uncertainties, including the machining and measurement processes variability, are not inherently incorporated. They can be quantified and minimized using Bayesian inference. Additionally, the traditional Kienzle model does not isolate the ploughing force from the cutting force. The model can be enhanced by incorporating the ploughing force component.

In this research, orthogonal turning is performed to measure cutting forces over a range of uncut chip thickness values. An extended Kienzle force model is proposed to include the ploughing force component and a non-linear least squares fitting (LSF) method is used to identify the force model coefficients using the experimental data. Additionally, the Bayesian Markov Chain Monte Carlo (MCMC) approach is used to develop a probabilistic model. The model is verified using forces measured under other cutting conditions. Finally, the LSF and Bayesian inference predictions are compared.

2 Orthogonal turning experiments

Tube turning experiments were performed on a Haas

10.1016/j.procir.2018.08.228

TL-1 CNC lathe; see Figure 1. The dry machining tests were completed using an uncoated insert SPGW09T308 with the ISO grade of P25, a rake angle of -10 *deg* and an edge radius of 20 μm. The tubular workpiece material was 1020 steel with an outer diameter of 25.4 *mm* and wall thickness of 2.1 *mm*. The corresponding chip width was 2.1 *mm*. Four feed values of h = {0.051, 0,076, 0.102, and 0.127} *mm/rev*, as well as three cutting speeds of V_c = {60, 80 and 100} *m/min*, were selected. The experiments were repeated three times for each cutting speed-feed combination. Therefore, the total number of experiments was 36.

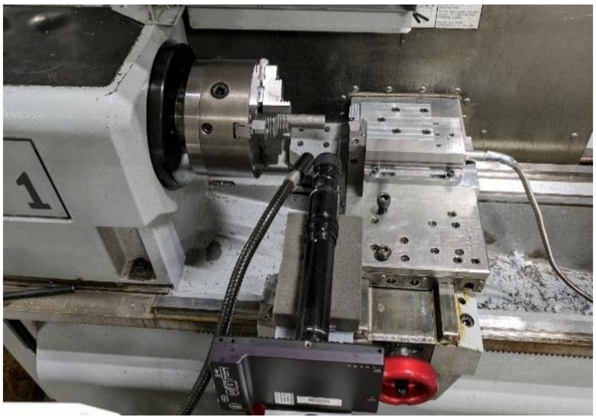

Figure 1. Orthogonal turning setup

A three-axis force dynamometer (Kistler 9257B) was used to measure the cutting force. Three data sets were used to identify the force model parameters and establish the prior for the probabilistic models, while the others were used for model verification. Figure 2 displays the tangential force component data for identification of the force model coefficients (using non-linear LSF) and prior training purpose. The mean is provided together with one standard deviation error bars. As can be seen, the forces increase with an increase in feed.

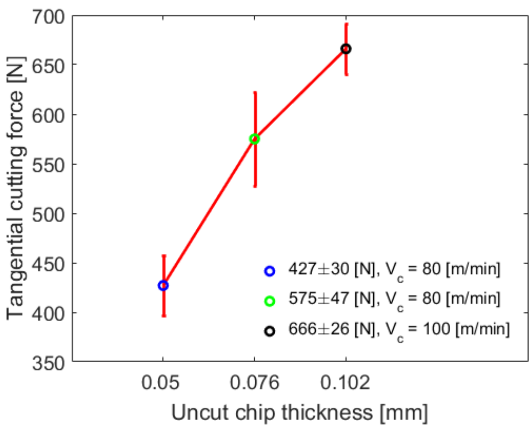

Figure 2. Tangential force components for training of the prior

3 Extended Kienzle force model

The Kienzle force model, Eq. (1), describes the relationship between the uncut chip thickness, h, and the tangential direction cutting force component, F_t, [2]:

$$F_t = K_{tt}.b.h^{1-c_t} \tag{1}$$

where 1-c_t, is a positive constant less than one and K_{tt} is the specific cutting force.

Since the cutting edge corner radius is nonzero, there is an increase of chip plastic deformation without material cutting for small chip thickness values. This phenomenon is referred to as ploughing [1]; see Figure 3.

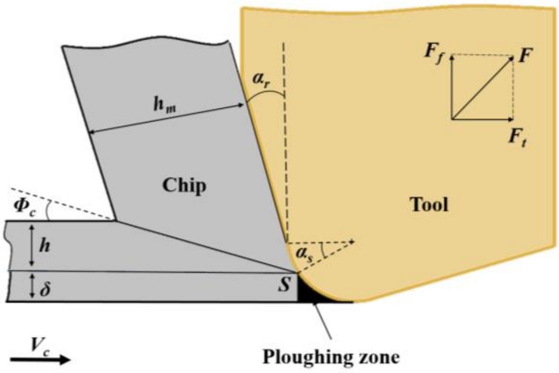

Figure 3. Schematic representation of ploughing

Ploughing can be included to the force model by adding a constant force coefficient that scales with the chip width, b.

$$F_t = \overbrace{K_{tt}.b.h^{1-c_t}}^{F_{t-shearing}} + \overbrace{K_{te}.b}^{F_{t-ploughing}} \tag{2}$$

In Eq. (2), K_{tt} is associated with shearing (cutting), while K_{te} is a ploughing (rubbing) term. The shearing component is dependent on the chip thickness, while the ploughing term is not.

4 Determination of model parameters

The parameters, K_{tt}, K_{te}, and c_t, are determined using the nonlinear LSF and Bayesian inference methods. The results are provided in the following sections.

4.1 Parameter determination using non-linear LSF

Figure 4 shows the force data curve fit (using Eq. (2)); the regression fit quality is R^2 = 0.99, where the lower and upper bounds for the fit parameters were selected to be 0 and 1000. Although the fit quality is high, and three training data were used to identify the force model coefficients, the approach was not able to identify the ploughing force coefficient, K_{te}.

4.2 Parameter identification using Bayesian inference (MCMC simulation)

Bayesian inference enables the prior, or initial belief about a parameter, to be updated by new experimental results. According to Eq. (3), the posterior probability, $p(x|y)$, is calculated by multiplying the prior, $p(x)$, by the likelihood function $p(y|x)$ and dividing by the normalizing function $p(y)$.

$$p(x|y) = \frac{p(x)\,p(y|\,x)}{p(y)} \quad (3)$$

Markov Chain Monte Carlo (MCMC) algorithms are used to approximate the posterior distribution of the parameters. The detailed application of MCMC to force prediction was reported in [3].

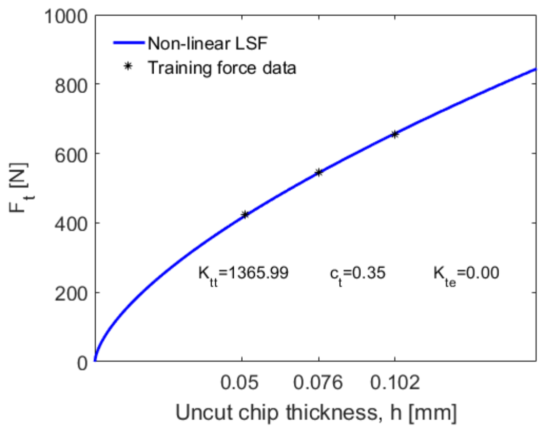

Figure 4. Non-linear LSF to determine the model parameters

To develop the probabilistic model for the extended Kienzle force model, prior values for the parameters K_{tt}, K_{te}, and c_t must be selected. The mean and standard deviation of the parameters were taken from [2] for a range of low carbon steel cutting operations:

1. $K_{tt} = 1560 \pm 96$ *MPa* (one standard deviation)
2. $c_t = 0.21 \pm 0.06$ (one standard deviation)

Waldorf *et al*. [4] described the "separation point on edge" model to study the ploughing force in orthogonal cutting processes. According to the model, the separation point, S, of the material in front of a rounded cutting edge is defined, where the upper part converts to the chip (cut chip thickness, h_m, and shear angle, Φ_c,) and travels along the rake face, while the lower part with the ploughing layer thickness, δ, remains attached to the workpiece; see Figure 3. The locating angle, α_s, for the separation point was reported to be approximately 65 *deg*. Therefore, the δ layer was calculated to be 2 μm (for a tool edge radius of 20 μm). The corresponding ploughing force coefficient can be approximated using the following steps.

a. K_{tt} and c_t are inserted in the shearing component of Eq. (2) to find the cutting force.
b. The force is set equal to the ploughing component of the equation.
c. The prior value of K_{te} is found by dividing the force by the chip width, b.

The corresponding prior value for the ploughing force coefficient is given as follows.

3. $K_{te} = 12 \pm 2.4$ *MPa* (one standard deviation)

Monte Carlo simulation was used to represent the prior for the cutting force model. Figure 5 illustrates the functional form of the prior mean value, two standard deviation (2σ) uncertainty intervals, and the training force data points. According to the figure, the prior mean function under-predicts the forces.

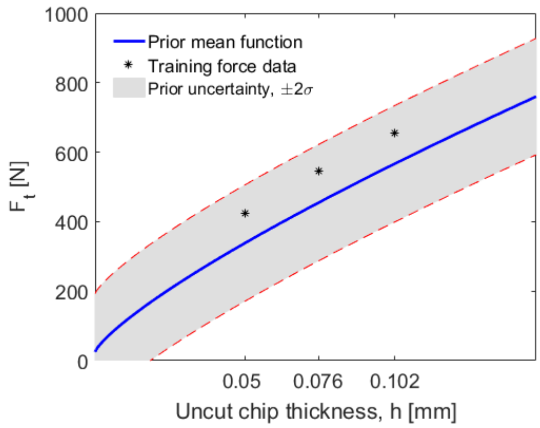

Figure 5. Prior function with $\pm 2\sigma$ standard deviation uncertainty intervals

The prior distribution of the model parameters, K_{tt}, K_{te}, and c_t, is updated by experiments results. MCMC simulation is used to update and calculate the posterior distribution of the parameters. The updating process of the parameters is performed using only $F_t = 427$ N, so that the uncertainty of the distributions is minimized after the training process.

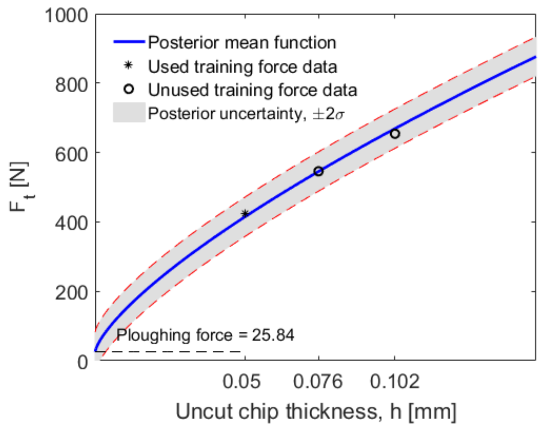

Figure 6. Posterior function with $\pm 2\sigma$ standard deviation uncertainty intervals

Figure 6 depicts the functional form of the posterior distribution with the mean and standard deviation of 2σ (R^2 = 0.989). The function approximates the shearing and ploughing components of the cutting force using only one training data, F_t = 427 N. This demonstrates that Bayesian inference is able to identify the model parameters with the minimum input thanks to the informative prior knowledge. The ploughing force is shown based on extrapolation to the zero chip thickness [5]. The corresponding mean values of the posterior parameters, K_{tt}, K_{te} and c_t, parameters, are 1597 *MPa*, 12.25 *MPa*, and 0.27, while the standard deviations are

66 *MPa*, 2.37 *MPa*, and 0.024, respectively. Furthermore, the uncertainty of the posterior function is significantly reduced.

The predicted ploughing force is verified using the simplified slip-line model [6], which has been proposed for turning processes:

$$F_{tp} = \tau . b . r_e . \tan\left(\frac{\pi}{2} + \frac{\alpha_r}{2}\right) \quad (4)$$

where F_{tp} is the ploughing force, τ is the shear stress, r_e is the edge radius, and α_r is the cutting edge rake angle. The τ parameter was computed to be 684 *MPa* using Merchant's force model [1]. From Eq. (4), F_{tp} is calculated to be 24.22 *N*, showing that the probabilistic model successfully approximates the ploughing force, 25.84 ± 2.37 *N*. Therefore, comparing the Bayesian and the non-linear LSF methods, the ploughing force identification was performed using the former, while it was not successful using the latter method, despite three training force data were used.

Table 1 shows the cutting conditions and forces used for the prediction purpose. According to the table, each row contains one to three force values as a result of repeated tests. Figure 7 illustrates the prediction of the cutting forces obtained under other cutting conditions using the posterior function. As can be seen, all of the force data appear within the uncertainty intervals.

Table 1. Cutting conditions and forces for prediction

No.	V_c (m/min)	f (mm/rev)	F_t (N)
1	80	0.051	415, 422
2	100	0.051	386
3	80	0.076	546, 576
4	100	0.076	500
5	80	0.102	647
6	100	0.102	667, 691
7	100	0.127	723, 730, 749

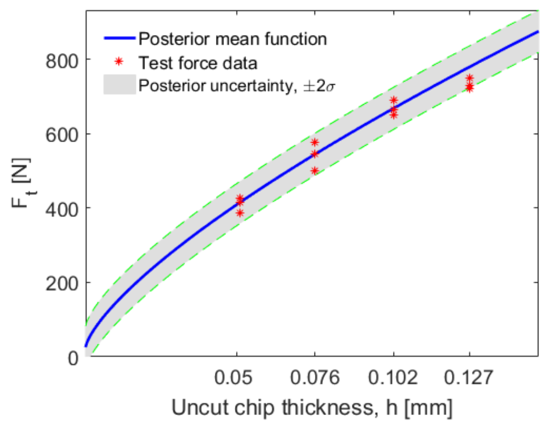

Figure 7. Posterior function for prediction with ±2σ standard deviation uncertainty intervals

5 Conclusions

In this research, cutting and ploughing force prediction was performed using nonlinear least squares fitting and Bayesian inference (MCMC simulation) methods. The prediction results were compared with orthogonal turning data and a simplified slip-line model. Comparing the fitting and inference approaches, it was shown that Bayesian inference can predict the cutting and ploughing forces with minimal initial data (one data point in this case) thanks to the informative prior knowledge. Further, the nonlinear fitting was not able to determine the ploughing force from the cutting force despite three training force data were used and a high fit quality (R^2 ~ 0.99) was achieved. This suggests that Bayesian inference offers a preferred approach to force modelling with minimum input and inherent uncertainty.

Acknowledgement

The corresponding author acknowledges the "abroad research stay" grant of Karlsruhe House of Young Scientists (KYHS), spent for research period in the University of North Carolina at Charlotte.

References

[1] Altintas Y., (2000). "Manufacturing Automation: Metal Cutting Mechanics, Machine Tool Vibrations, and CNC Design", Cambridge University Press, Cambridge, Section 2.8.1.

[2] Denkena B., Toenshoff H.K., (2011). "Spanen-Grundlagen", springer-Verlag, p. 56. Book name in English language: "Chip removal-Fundamentals".

[3] Karandikar J., M., Abbas AE., Schmitz TL., (2014). "Tool life prediction using Bayesian updating. Part 2: Turning tool life using a Markov Chain Monte Carlo approach", Precision Engineering 38 (1), 18-27.

[4] Waldorf D.J., DeVor R.E., Kapoor S.G., (1999). "An evaluation of ploughing models doe orthogonal machining", journal of Manufacturing Science and Engineering, Vol. 121, pp. 550-558.

[5] Albrecht P., (1960). "New developments in the theory of the metal cutting processes", Part 1. The ploughing process in metal cutting, ASME Journal of Engineering for Industry 82, pp. 348–357.

[6] Waldorf D.J., (2006). "A Simplified Model for Ploughing Forces in Turning", Journal of Manufacturing Processes, Vol. 8/No. 2.