International Journal of Machine Tools and Manufacture 136 (2019) 45–61

Contents lists available at ScienceDirect

International Journal of Machine Tools and Manufacture

journal homepage: www.elsevier.com/locate/ijmactool

Statistical calibration and uncertainty quantification of complex machining computer models

Patxi Fernandez-Zelaia[*,1], Shreyes N. Melkote[1]

George W. Woodruff School of Mechanical Engineering, Georgia Institute of Technology, Atlanta, GA, United States

ARTICLE INFO

Keywords:
Finite element
Constitutive modeling
Calibration
Surrogate modeling
Uncertainty quantification
Machining

ABSTRACT

Finite element based machining process models are used in research and industry for process design and optimization. These models require a constitutive description of the material behavior to accurately model and predict process responses such as cutting forces, temperatures, and residual stress. Calibration of these models to low-strain uniaxial dynamic compression experiments can be troublesome since the machining process generally imposes much larger strains than uniaxial compression. Calibration of finite element models directly to machining data is generally difficult since the models are computationally expensive and nonlinear optimization methods for estimating the unknown calibration parameters yield non-unique solutions and require many iterations. In this work we utilize a nonstationary Gaussian Process surrogate model to emulate the finite element response and calibrate to experimental orthogonal cutting tests using a Bayesian inference framework. We assume that the material yield behavior can be described by the Johnson-Cook material flow model. We find that the nonstationary Gaussian Process model is an good surrogate for the complex finite element model. Cutting forces measured from orthogonal tube turning experiments were used for calibration. Validation is performed using a separate response variable - the cut chip thickness. Calibration results illustrate a preference for material models with low hardening rates, which alleviates issues such as over-prediction of strain hardening behavior when using the Johnson-Cook material flow model. The Bayesian formulation also captures the uncertainty in the Johnson-Cook parameters, which can be used to quantify the uncertainty in the machining process responses. The methods presented here are general and can be used for more complex constitutive and tribological models for machining and other complex manufacturing processes.

1. Introduction

Finite element (FE) models of machining processes have enabled the detailed simulation of complex cutting physics [1]. These numerical models serve as useful tools for the design and optimization of manufacturing processes. The FE models incorporate plasticity, contact mechanics, and heat transfer physics. Therefore, to accurately model a specific machining process, accurate models of these three components are required. A great deal of effort in the machining community has been spent on the plasticity law (flow law) [2–8] and, to a lesser extent, on the tribological behavior [8,9]. The difficulty in establishing flow laws appropriate for machining is that the thermo-mechanical conditions imposed on the material during machining cannot be emulated by standard mechanical tests. During machining, strains between [1–10] can be expected with strain rates on the order of $10^4 - 10^6\ s^{-1}$ and high temperatures due to plastic work. Tension/compression split-Hopkinson bar tests can impose strains typically as high as ~ 0.5 with rates as high as $10^4\ s^{-1}$ [10,11]. Taylor-impact tests can impose higher rates, $10^5\ s^{-1}$, and larger local strains up to ~ 2. However, it is difficult to directly determine the flow stress from these experiments [12,13]. Similarly, split-Hopkinson shear tests can impose large shear strains and strain rates [14] but the flow stress cannot be directly observed; instead a model must be invoked to indirectly infer the uniaxial equivalent flow stress. For instance, the von Mises criterion assumes that the stress may be converted via $\sigma = \sqrt{3}\tau$ and strains via $\varepsilon = \gamma/\sqrt{3}$. Applying this to Johnson and Cook's original OFHC-Cu data [10] yields reasonable results. However, when comparing with data in Ref. [14] the model shows significant disparities. This discrepancy is most likely material specific, and sensitive to the dependence of the yield surface on stress triaxiality [15], and sensitive to the specimen geometry.

Therefore, identification of material-specific plasticity law directly from machining experiments is an attractive strategy. The difficulty in

* Corresponding author.
E-mail addresses: pfz3@gatech.edu (P. Fernandez-Zelaia), shreyes.melkote@me.gatech.edu (S.N. Melkote).
[1] George W. Woodruff School of Mechanical Engineering.

https://doi.org/10.1016/j.ijmachtools.2018.09.004
Received 14 June 2018; Received in revised form 1 September 2018; Accepted 17 September 2018
Available online 21 September 2018
0890-6955/

doing so however is that the machining process is complex and hence, like Taylor impact and shear configuration split-Hopkinson tests, the complexity of the experiment confounds direct assessment of the flow stress relationship. The first work to calibrate a flow law to machining data is that by Özel and Zeren [4]. In this work the authors utilize the Johnson-Cook (JC) [10] model to describe the material flow stress and use Oxley's model [16] to describe the chip formation process. The use of Oxley's analytical model alleviates the need for FE models and allows for efficient iterative error minimization to obtain estimates of the unknown JC parameters. Ulutan and Özel later extended this methodology to incorporate the use of 3D FE based turning simulations to calibrate Ti6Al4V and IN100 plasticity models [5]. The optimization methodology in their work iteratively adjusts the unknown plasticity coefficients until a convergence criterion for the difference between the simulation and experimental forces is satisfied. This process is however extremely costly as acknowledged by the authors who note that each simulation required 50 *hrs* to complete (utilizing computing resources available in 2013). In comparison, our 2D orthogonal cutting simulations require 1–6 h per simulation depending on the material settings of each run. Özel, Arisoy, and Guo later extended this methodology to also include a microstructure sensitive plasticity law [6].

There have been a few works in the machining community which employ FE surrogate models for calibration. Kloche, Lung, and Buchkremer employed a step-wise approach for calibrating the JC model parameters where first the strain hardening terms were calibrated to uniaxial quasi-static room temperature data [17]. This was followed by a tabular/interpolation calibration of the rate hardening and thermal softening terms utilizing machining experiments and FE simulations. Tool-chip interface friction was assumed to follow empirical trends reported in the literature. The appeal of this approach is in its simplicity. However, this is also the main limitation since the model decomposition is only possible for simple model forms. As the number of unknown parameters increases, it is unlikely that such a simplified linear interpolation strategy would be suitable, especially if there are strong interactions between the terms in the model. Agmell, Ahadi, and Stahl employed a Kalman filter to identify the JC model parameters [18,19]. A Coulomb friction coefficient of 0.4 was used in all simulations. To compute the discrepancy between the FE simulations and experiments, a 4^{th} order polynomial surrogate model was built from the FE simulations. The polynomial model modeled the change in machining responses relative to a reference or nominal setting, which is similar to work found in Refs. [20,21]. The influence of each of the model parameters in Refs. [18,19] however was assumed to have no interactions in the surrogate model and therefore can only capture independent effects. In general, polynomials as a basis for developing surrogate models are limited to lower order polynomials and only a few FE model parameters. This is due to the curse of dimensionality i.e. as the dimensionality of the problem increases the number of terms in a polynomial expansion increases exponentially. The authors in Refs. [18,19] circumvent this problem by neglecting interaction terms, which severely limits the utility of the surrogate model. A recent study employed the Response Surface Methodology (RSM) to build a surrogate FE model for calibration [22]. Again, this strategy is fundamentally built on regression of polynomials, which becomes intractable in high dimensions. Furthermore, RSM was developed for physical experiments, which contain observation errors. In contrast, FE model simulations are deterministic and do not have such errors. Therefore, there is a risk that RSM mistakenly fits the FE model responses to an overly smooth manifold and attributes nonlinearities present in the FE model to random error. Furthermore, these surrogate modeling approaches assume some parametric form: linear interpolation [17], 4^{th} order polynomial with no interactions [18,19], and quadratic functions [22]. If the true response is not well described by the assumed model forms then the surrogates are inadequate. For these reasons, statisticians favor non-parametric Gaussian process models for calibration [23,24]. From a model calibration perspective, a limitation shared by the foregoing machining calibration studies is that they only produce point estimates and cannot yield confidence intervals for the obtained quantities. This is perhaps one reason why there exists a large range of reported JC model parameter values in the literature for the same material systems [8]. Additionally, the calibration methodologies employed in these studies seldom consider the interaction with the assumed friction model.

The advantage in utilizing a FE based machining model for identification of the constitutive model parameters is that much more complex physics can be modeled. Analytical models require the use of assumptions and simplifications to produce an easy-to-evaluate algebraic result. The trade-off is that FE simulations are computationally expensive and so the choice of model is dependent on the goals, objectives, and computational budget of the user. A nonlinear regression of a model to experimental data requires iterative (nonlinear) optimization, which renders the direct use of an FE model to be extremely costly. Therefore, traditional calibration of plasticity laws from machining experiments cannot be performed efficiently through direct use of FE models.

The seminal work of Kennedy and O'Hagan addresses this difficulty associated with calibration of computationally expensive computer codes [23]. The inefficiency of an iterative procedure, each step with multiple complex code evaluations, is alleviated instead by only evaluating the code prior to optimization. The user can decide on a reasonable number of model evaluations, which are performed over a suitable *experimental design*. From these evaluations, a Gaussian Process (GP) model of the computer code can be built. The statistical GP model can be interpreted as a surrogate model of the expensive code. The model calibration step is performed by jointly considering both experimental data and model outputs over the experimental design. GP models have good generalizing properties for emulating complex functions. Furthermore, because they are statistical in nature, GP models can also provide confidence bounds associated with function estimates. Among the large class of surrogate models, this attribute makes GPs distinctly unique. This statistical feature enables practitioners to also consider the uncertainty associated with surrogate model predictions. Just one example where this is useful is for risk-based decision making. In the context of deterministic computer codes, GP models are particularly attractive because they can be shown to be *interpolators* [25]. This is critical since the output of a deterministic simulation has no observation error and thus this information should be preserved exactly. This is distinctly different from regression methods. GP models have been utilized throughout engineering to model many complex systems. A few examples include: cardiac cells [24], large eddy combustion processes [26], knee prosthesis [27], spherical indentation [28], and machined surface roughness [29].

In this work we seek to establish an efficient method for calibrating orthogonal cutting FE models and quantifying the uncertainties of the material flow law used in the FE models. First we establish an appropriate GP model for emulating the simulated cutting and thrust forces. Then we employ a Bayesian inference framework to solve the inverse problem and establish the posterior probability distribution of the material flow law parameters. The approach is validated by performing additional FE simulations at the obtained flow law solution and comparing the simulated deformed cut-chip thicknesses to experimental observations.

2. Experimental methods

Tube turning experiments were performed to measure the cutting and thrust forces under idealized orthogonal cutting conditions. All experiments were performed in a CNC lathe (Okuma Spaceturn LB2000EX). Bars of Al6061-T6 (BHN 95) were machined to an outer diameter of 30.48 mm and a wall thickness of 2 mm. In order to obtain the forces over a wide range of strains, strain rates, and temperatures, cutting speeds of 12, 20, 30 and 60 $m\cdot min^{-1}$ were used. Cutting tools