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Article

An analytical Modeling for Designing the Process Parameters for Temperature Specifications in Machining

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Abstract: Different process parameters can alter the temperature during machining. Consequently, selecting process parameters that lead to a desirable cutting temperature would help to increase the tool life, decrease the tensile residual stress, and controls the microstructure evolution of the workpiece. An inverse computational methodology is proposed to design the process parameters for specific cutting temperature. A physics-based analytical model is used to predict the temperature induced by cutting forces. To calculate the temperature induced by the deformation in the shear zone, a moving point heat source approach is used. The shear deformation and chip formation model is implemented to calculate machining forces as functions of process parameters, material properties, and etc. The proposed model uses the analytical model to predict the cutting temperatures and applies a variance-based recursive method to guide the inverse analysis. In order to achieve the cutting process parameters, an iterative gradient search is used to adaptively approach the specific temperature by the optimization of process parameters such that an inverse reasoning can be achieved. Experimental data are used to illustrate the implementation and validate the viability of the computational methodology.

Keywords: Inverse analysis; Temperature prediction; Process parameters; Cutting speed; Depth of cut

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1. Introduction

Temperature measurement and prediction have been a major focus of machining research for several decades [1, 2]. Temperature generation during machining has a substantial effect on the tool wear, tool distortion, residual stress, and microstructure evolution of the workpiece. During cutting metals, a considerable amount of the input power is transferred into heat through plastic deformation of the workpiece material, the friction of the chip on the tool and the friction between the tool and the workpiece. The heat generated in the cutting zone can influence the cutting tool and the of the workpiece qualities [3].

The dissipated heat can considerably change the microstructure of the workpiece. Cutting process parameters such as cutting speed, feed rate, and depth of cut have a substantial influence on machining temperature. Increase in cutting temperature results in greater tensile residual stress on the surface of a machined component [4]. As a result, choosing viable cutting process parameters can significantly help to have a desired cutting temperature.

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Many works have been done in determining the temperature distribution in machining. In the past few decades, numerical methods, such as finite element method (FEM) is utilized for the temperature prediction in machining since it provides a better understanding of the heat generation in the cutting zone, resulting stresses, temperature fields, and chip formation mechanisms. Lei et al. developed a thermomechanical two-dimensional FE model for the orthogonal cutting process with continuous chip formation [5]. Umbrello et al. developed a FE model to predict temperature when steady-state conditions were reached. Pure thermal simulation is conducted in order to determine the heat transfer coefficient between tool and workpiece in steady-state condition. The obtained heat transfer coefficient was used in a thermomechanical simulation for temperature prediction [6]. Özel et al. developed a FE model to investigate the influence of cutting-tool edge roundness on the temperature field at tool–chip and tool–workpiece interfaces [7].

Many researches developed analytical models to predict the temperature in machining process. Komanduri et al. developed an analytical model for temperature prediction. The obtained temperature is combined effects of the shear plane heat source at the primary shear zone and the frictional heat source at the secondary shear zone [8]. Liang et al. developed a physics-based analytical model to predict temperature distribution by considering the tool thermal properties and the tool wear effects [9]. Huang et al. developed a cutting temperature model with an assumption of non-uniform heat intensity and partition ratio and reported improved accuracy upon validation [10].

Considerable accuracy is achieved from the FEM, but computational efficiency is low. On the other hand, the analytical model provides accurate results. The high computational efficiency and easy implementation are the other advantages of the analytical models for the machining process modeling [11, 12].

The process parameters need to be selected in order to achieve a desirable temperature in machining. Randomly choosing the process parameters and predicting the cutting temperature through analytical model or finite element analysis repeatedly is not a reasonable way to achieve a desirable temperature during machining. Nowadays, most of the researchers are using the trial and error method in order to have a desirable workpiece performance. This method is not only time consuming, but also expensive. As a result, an inverse analysis is proposed in addition to the forward analysis to identify the viable solutions of process parameters that can achieve a specific performance.

An inverse analysis is successfully used for identification of mechanical properties which are hard to be measured in experiments [13-16]. Pujana et al. used an inverse analysis to identifies the coefficients of constitutive equations of flow stress in orthogonal cutting and used finite element method to evaluate the results [17]. Denkena et al used the inverse analysis to predict the constitutive parameters of the Johnson-Cook's flow stress model . [18]. Chen et al. chose cutting force and chip thickness as targets and optimized the inverse analysis of determining Al6063 constitutive model coefficients [19]. Sampsa et al. also used the inverse analysis to predict Johnson-Cook model parameters with four target performances including cutting force, tangential force, resultant force, and cutting temperature [20]. Mirkoohi et al. [21] used an inverse analysis to predict the process parameters in turning of Ti-6Al-4V in order to achieve a desirable cutting force.

There are significant works on literature on modeling of the temperature during the machining process. However, the lack of enough research on selecting the viable process parameters which result in a desirable temperature is noticeable. The influence of cutting process parameters on temperature is profound. Therefore, a systematic approach is required to obtain these cutting process parameters. Determining the process parameters to ensure resulting cutting temperature can significantly help to have a desirable workpiece microstructure, and also residual stress [22].

In order to achieve desirable cutting temperature, it is required to select the process parameters in a systematic manner. A physics-based model is used to predict the temperature. The heat comes from the primary shear zone and the tertiary shear zone between tool and workpiece. An imaginary moving heat source approach is used to calculate the temperature field induced by the deformation in the shear zone [23] . Next, an iterative gradient search procedure is set up to adaptively approach the specific temperature by the optimization of process parameters such that an inverse reasoning can be achieved. An iterative gradient search based on Kalman filter identifies two process

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parameters including depth of cut and cutting velocity and achieves the optimal solution for the temperature.

To illustrate the implementation method and validate the viability of the proposed method, experimental data are used. These data are used as a starting point for inverse analysis. The proposed model achieves the closest temperature to the experimental temperature by the optimization of process parameters and inversely designs the cutting process parameters such as cutting velocity and depth of cut.

2. Approach and Methodology

2.1. The Forward Analysis: Temperature Modeling

The temperature gradient induced by the cutting process can have a significant effect on the residual stress, tool wear, and microstructure evolution of the workpiece. The increased in cutting temperature in machining result in greater tensile residual stress on the surface of a machined component [24]. In modeling of the workpiece temperature, two heat sources are assumed to exist. The first is the primary heat source generated from the shear zone [25]. The second heat source is a result of rubbing between the tool and the workpiece. To calculate the temperature field induced by the deformation in the shear zone, a moving heat source approach is used. The temperature rises in the workpiece due to shear deformation is the combined effects of the shear heat source and moving heat source [23], which can be obtained as

$$\Delta T_{shear}(x,z) = \frac{V_c q_s}{4\pi K a}\int_0^L e^{\frac{-(x-l_i\sin\varphi)V_c}{2a_{workpiece}}} \times \{\sqrt{(x-l_i\sin\varphi)+(z-l_i\cos\varphi)}+\sqrt{(x-l_i\sin\varphi)+(z+\cos\varphi)}\}dl_i \quad (1)$$

where L is the shear length, $L = \frac{t}{\sin\emptyset}$, $\emptyset$ is the shear angle, t is undeformed chip thickness, $\emptyset = \varphi - \frac{\pi}{2}$, V_c is the cutting speed, a is the workpiece thermal diffusivity, K is workpiece thermal conductivity, and K_0 is the modified second Bessel function. The average shear stress in the shear zone can be approximated as

$$q_s = \frac{(F_c\cos\varphi - F_t\sin\varphi)V_{cut}\cos\varphi}{tw\cos(\varphi-\alpha)\csc\varphi} \quad (2)$$

where, F_c and F_t are the cutting forces. The cutting forces consist of chip formation and plowing force which can be calculated from shear deformation and chip formation model [26]. In this model, the cutting plane is considered as a thick cutting band. As a result, the effects of material deformation and work hardening can be considered.

A moving heat source can also be used to calculate the heat generated in the rubbing zone. To satisfy the insulated boundary condition on the workpiece surface, an imaginary heat source is imposed as coinciding with the original rubbing heat generation. The temperature rise induced by the tool–workpiece rubbing can be calculated as

$$\Delta T_{rubbing}(x,z) = \frac{\gamma V_c q_{rub}}{2\pi K_w a_w} \times \int_0^{CA} K_0 \exp(-\frac{(x-s)V_c}{2a_w}\{[\sqrt{(x-s)^2+(z)^2}]\}ds \quad (3)$$

where CA is the work-dead zone interface length which is calculated using slip line model [27]. γ is heat partition coefficient that transferred to the workpiece. According to Barber [28], the heat partition coefficient could be calculated as

$$\gamma = \frac{\rho_w C_w\sqrt{K_w}}{\rho_w C_w\sqrt{K_w}+\rho_{tool}C_{tool}\sqrt{K_{tool}}} \quad (4)$$

where the subscript ρ_w, Cw, and Kw are the workpiece material density, heat capacity, and thermal conductivity, respectively. ρ_{tool}, C_{tool}, and K_{tool} are corresponding the tool properties. The rubbing stress q_r is determined from the plowing force P_c in the cutting direction as

$$q_r = \frac{P_c V_c}{w\ CA} \tag{5}$$

The plowing force *Pc* can be calculated from traditional cutting mechanics [29], and *w* is the width of cut. The total temperature rise in the workpiece can be obtained by superimposing the two temperature effects from rubbing and shear as

$$\Delta T = \Delta T_{shear} + \Delta T_{rubbing} \tag{6}$$

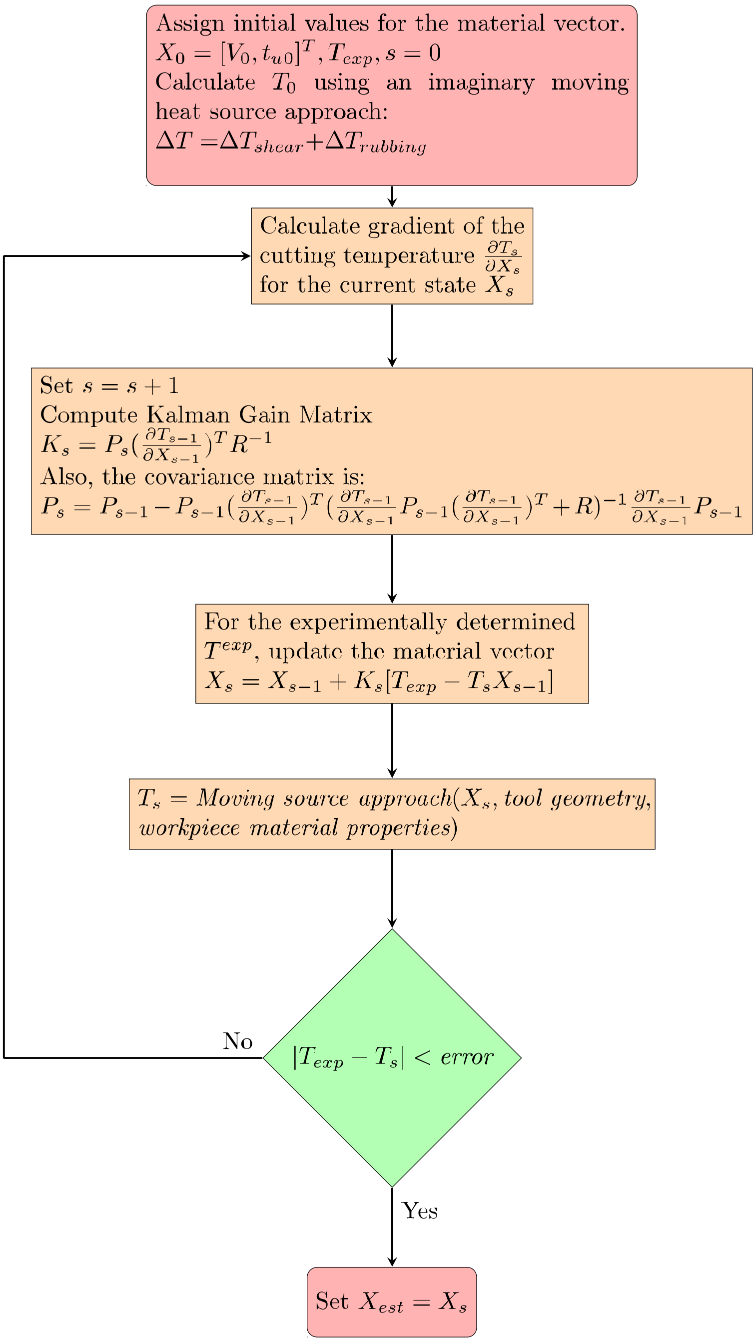

Figure 1. Fellow diagram of proposed inverse model

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2.2. Inverse Analysis: An iterative gradient search based on Kalman filter:

The proposed algorithm estimates two unknown cutting process parameters which are the depth of cut (t_u) and cutting tool velocity (V) on the basis of experimentally measured cutting temperature. Fig. 1 is demonstrated the proposed approach. The two unknown constants are represented as $X = (V, t_u)^T$. At time s = 0, the initial estimates are $X_0 = (V_0, t_{u0})^T$. These initial estimates of cutting process parameters are used to calculate the initial cutting temperature. Then the obtained cutting temperature is compared to the desired temperature that is assigned at the first of the proposed model.

The estimation of subsequent cutting process parameters is obtained as

$$\mathrm{X_s} = \mathrm{X_{s-1}} + \mathrm{K_s}\left[\mathrm{T_{exp}} - \mathrm{T_s}\left(\mathrm{X_{s-1}}\right)\right] \tag{7}$$

K_s is the Kalman gain matrix, *Texp* is the vector containing the experimentally determined temperature in machining. $T_s\,(X_{s-1})$ is the vector containing the cutting temperature computed from the previous iteration using forward model as explained in section 2.1.

$$\mathrm{T_{exp}} = [\ \mathrm{T}\ ] \tag{8}$$

$$\mathrm{T_s}\left(\mathrm{X_{s-1}}\right) = \left[\mathrm{T^{s-1}}\right] \tag{9}$$

The Kalman gain matrix is computed as

$$\mathrm{K_s} = \mathrm{P_s}\left(\frac{\partial \mathrm{T_{s-1}}}{\partial \mathrm{x_{s-1}}}\right)^{\mathrm{T}} \mathrm{R^{-1}} \tag{10}$$

$$\mathrm{P_s} = \mathrm{P_{s-1}} - \mathrm{P_{s-1}}\left(\frac{\partial \mathrm{T_{s-1}}}{\partial \mathrm{x_{s-1}}}\right)^{\mathrm{T}}\left[\left(\frac{\partial \mathrm{T_{s-1}}}{\partial \mathrm{x_{s-1}}}\right)\mathrm{P_{s-1}}\left(\frac{\partial \mathrm{T_{s-1}}}{\partial \mathrm{x_{s-1}}}\right)^{\mathrm{T}}\mathrm{R}\right]^{-1} \times \left(\frac{\partial \mathrm{T_{s-1}}}{\partial \mathrm{x_{s-1}}}\right)\mathrm{P_{s-1}} \tag{11}$$

The Kalman gain matrix is multiplied by the differences between the experimental and the iterated temperature to update the unknown depth of cut (t_u) and velocity (V), as shown in Eqn. 10. For the two unknown cutting process parameters (t_u and V) and the known cutting temperature, the size of the Kalman gain matrix is 2×1. $\frac{\partial T_s}{\partial X_s} \in \mathbb{R}^{2\times1}$ contains the gradients of T with respect to unknown cutting process parameters. Furthermore, P_s is the simulation covariance matrix, which is the range of the unknowns at increment s, and R is the error covariance matrix, which is the size of the simulated error. P_s is updated at each step, whereas R is a non-iterative parameter that is prescribed at the initialization stage. Due to the sensitivity of the convergence rate of the Kalman algorithm to the value of P_s and R, it is essential that these two matrices be assigned properly. The initial simulation covariance matrix P_0 and the error covariance matrix R are set to be

$$\mathrm{P_0} = \begin{bmatrix} \Delta \mathrm{V}^2 & 0 \\ 0 & \Delta \mathrm{t_u}^2 \end{bmatrix} \tag{12}$$

$$\mathrm{R} = [\ \mathrm{T}^2] \tag{13}$$

where, ΔV^2 and Δt_u^2 state the predicted ranges of the unknown process parameters. In the current analysis, the diagonal components of R are chosen on the basis of the experimentally determined cutting temperature. The error threshold is used as stopping strategy for this approach. In each iteration, the error between experimental cutting temperature and predicted is computed. If the less error than the desired error is obtained, the algorithm will be terminated.

3. Results and Discussion

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In order to illustrate the implementation and also to validate the viability of the computational methodology, the orthogonal experimental data are selected from Umbrello et. al. [6]. Two chromel/alumel thermocouples (K-Type) with a diameter of 0.5 mm are embedded in the tool. The temperatures are acquired by an analogical/digital converter. The material in these experiments is AISI 1045 steel. The material properties of AISI 1045 steel is listed in Table 1 [24]. The cutting speed ranging from 50 to 100 m/min. Three different values of depth of cut (0.05, 0.1, 0.15 mm/rev) are used. The rake angle is $-10°$. The cutting width for all the cases is 3 mm, and the clearance angle is $11°$.

Table 1. Thermal and mechanical properties of AISI 1045

Density (kg/m3)	7800
Young's modulus (GPa)	190
Thermal expansion coefficient(°C−1)	11.2
Heat capacity (J/kg·°C)	470
Thermal conductivity (W/m·°C)	49.8
Poison's ratio	0.29

In each loop, both direct analysis and inverse analysis are conducted once, and the predicted temperature is compared to the experimental measurement. By varying the depth of cut, and velocity the temperature data from the experiment, and the proposed model are listed in Table 2. The proposed inverse model tries to change the process parameters in each step in the direction that the model predicts the closest temperature to the desired temperature. The predicted cutting temperature and experimental cutting temperature are plotted in Fig. 2. The experimental cutting temperatures are the desirable values. The predicted cutting temperatures tend to be higher than the experimental values. The maximum error between the experiment and model is for sample 3, which is 9.56%. The main reason for these errors comes from the gap between the analytical model and experimental measurements in the forward analysis.

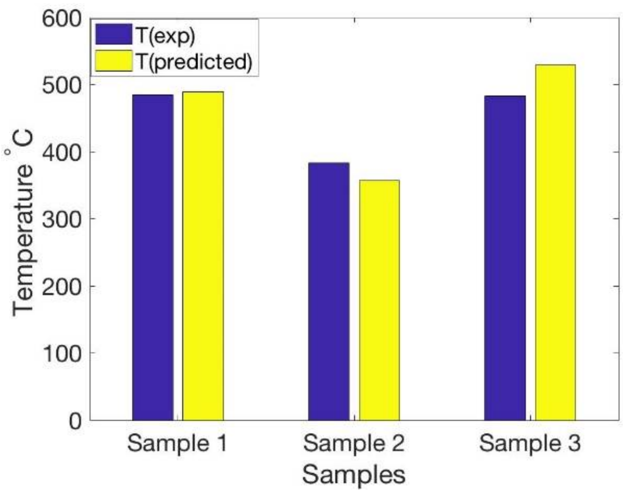

Figure 2. Comparison of predicted cutting temperature with experiments for a rake angle of $-10°$ and different depth of cut and velocity.

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Table 2. Comparison of temperature and process parameter

Samples	1	2	3
T (exp)/°C	485	383	483
T (model)/°C	489.59	357.44	529.18
V (exp)m/s	1.66	0.83	0.83
V (model)m/s	6.07	4.42	1.6
t_u (exp)/mm	0.1	0.05	0.15
t_u (model)/mm	1.2	0.12	0.058

The goal of the proposed model is to design the cutting velocity and depth of cut for a desired temperature. The initial guess $X_0 = (V_0, t_{u0})^T$ is chosen arbitrarily. For the first sample, as shown in Fig. 3 the initial depth of cut is 0.1 mm and it is converged to 1.2 mm after a very short number of iterations. This value is far from the initial specified depth of cut. The cutting velocity is plotted as a function of the number of iterations in Fig. 4. For sample 1, the initial guess is 0.5 m/s and it is converged to 6.07 m/s at a very low number of iterations, which shows the efficiency of the proposed model. This worth to note that for a given temperature, many combination of process parameters can be estimated in order to satisfy the given temperature. The cutting temperature is obtained by optimization of the process parameters, as illustrated in Fig. 5. The optimal solution for sample 1 is 489.59°C. The temperature measured from experiment is 485°C.

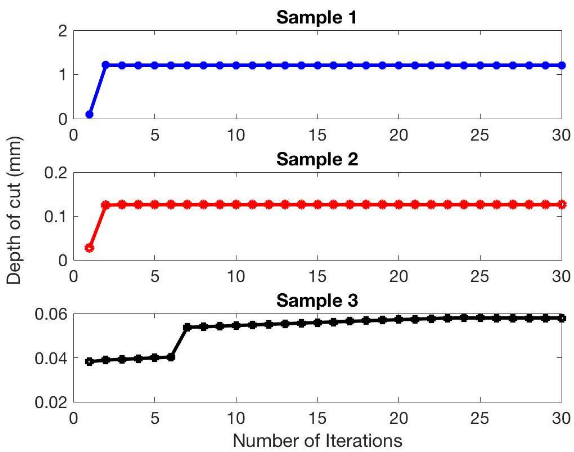

Figure 3. Evolution of depth of cut as a function of number of iterations.

For the second sample, the temperature measured from the experiments is 383 °C. This value of temperature is chosen as a desired value. The initial guess is $X_0 = [1.5, 0.05]^T$. After a very short number of iterations, it is converged to $X_s = [4.42, 0.13]^T$. The optimal predicted temperature from the proposed model is 357.44°C.

For the third sample, the temperature measured from the experiments is 483 °C. This value of temperature is also chosen as a desired value. The initial guess is $X_0 = [1.5, 0.05]^T$, and it is converged to $X_s = [1.6\,, 0.057]^T$. The optimal calculated temperature is 529. 18°C.

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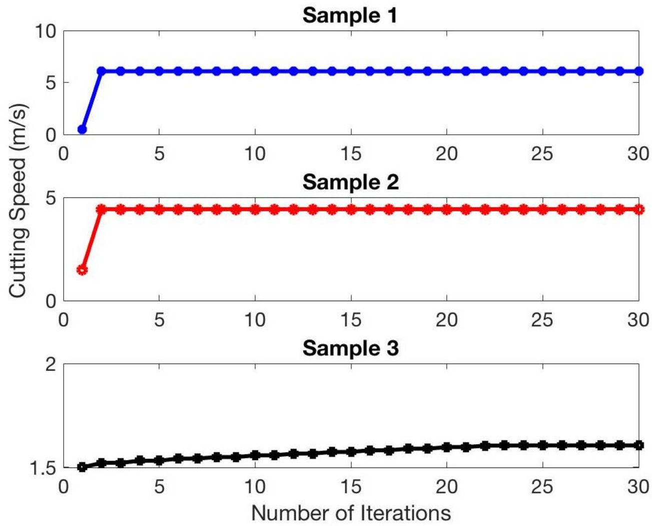

Figure 4. Evolution of cutting velocity as a function of number of iterations

By estimating the process parameters at each iteration for each sample as shown in Fig. 3 and Fig. 4 the temperature during the machining can be obtained using the forward model as explained in section 2.1. The obtained temperature is plotted as a function of number of iterations for each process parameters for all three samples as shown in Fig. 5. In sample 1 and 2, the temperature converges after two number of iterations. In sample 3 the temperature converges after eight number of iterations which shows the efficiency of the proposed model.

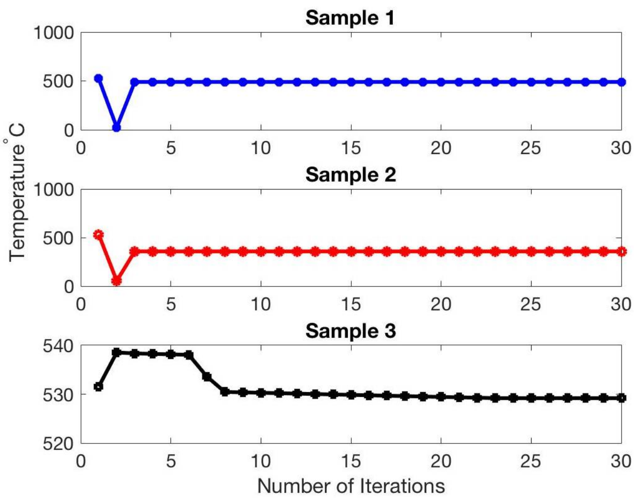

Figure 5. Evolution of temperature as a function of number of iterations

The shear deformation and chip formation model, as proposed by Oxley, is used to predict the cutting forces for a desirable temperature in machining. The cutting force and thrust force are plotted in Fig. 6 and Fig 7. The cutting force and thrust force follow the same trend, and they converge at very short number of iterations. The corresponding shear angle is also plotted in Fig. 8. The shear angle in these three samples has the range between 19° in sample 3 to 24° in sample 1.

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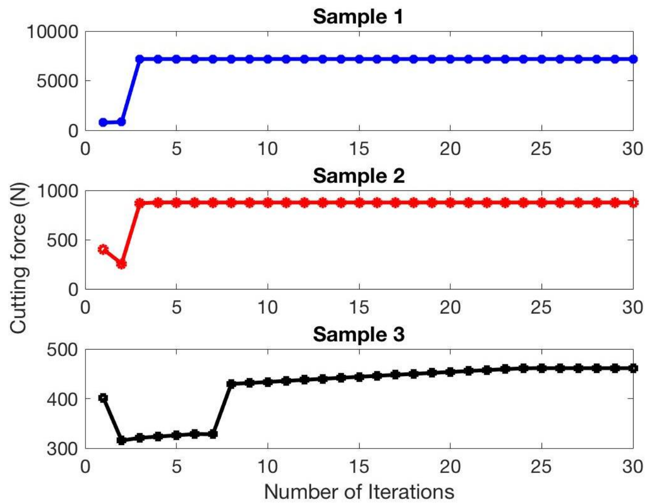

Figure 6. Evolution of cutting force as a function of number of iterations

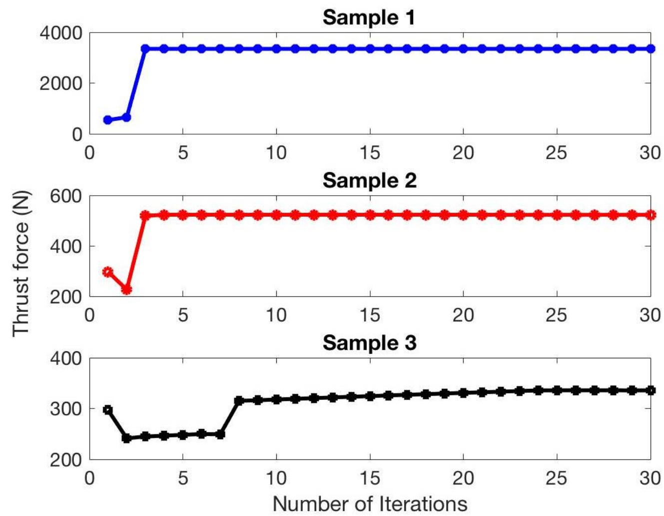

Figure 7. Evolution of cutting force as a function of number of iterations

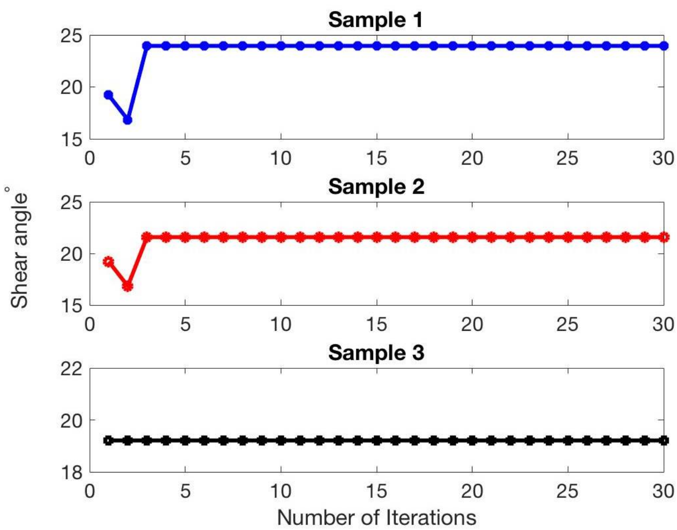

Figure 8. Evolution of shear angle as a function of number of iterations.

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4. Conclusions

A physics-based model along with an iterative gradient search based on Kalman filter algorithm is utilized to determine the cutting process parameters for the desired temperature. Having a desirable temperature in the machining process can significantly reduce the tensile residual stress, tool wear, and it helps to control the microstructure evolution of the workpiece.

In order to obtain the desirable cutting temperature, the viable cutting process parameters should be selected. A physics-based model is used to obtain the cutting temperature using an imaginary heat source approach.

The gradient search procedure is set up to adaptively approach the cutting temperature by the optimization of process parameters such that an inverse reasoning can be achieved. Experimental data are used to illustrate the implementation and also validate the viability of the computational methodology.

The predicted cutting temperature is considerably close to the experimental data. The obtained cutting process parameters are far from the initial assigned process parameters. In other words, the proposed model can obtain the process parameters even when the initial guess is far from the solution. The cutting velocity and depth of cut are converged at a very short number of iterations which shows the efficiency of the proposed model.

In each iterative step, a new cutting force, and thrust force are generated which was calculated using shear deformation and chip formation model for a given cutting temperature. Moreover, the shear angle is obtained using an iterative algorithm. The proposed analytical model provides a fast computation of process parameters for a specific temperature without needing costly experiments, and time consuming finite element analysis. Furthermore, selecting viable cutting process parameters which results in a specific cutting temperature, can significantly influence the tool wear, input power, and also can lead to having a desirable microstructure.

Author Contributions: E.M. conceived and developed the proposed analytical model, extracted and analyzed the data, and wrote the paper. P.B provided general guidance. S.Y.L. provided general guidance and proofread the manuscript writing.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Yen, Y.-C., A. Jain, and T. Altan, A finite element analysis of orthogonal machining using different tool edge geometries. Journal of materials processing technology, 2004. 146(1): p. 72-81.
2. Sutter, G., et al., An experimental technique for the measurement of temperature fields for the orthogonal cutting in high speed machining. International Journal of Machine Tools and Manufacture, 2003. 43(7): p. 671-678.
3. Ng, E.-G., et al., Modelling of temperature and forces when orthogonally machining hardened steel. International Journal of Machine Tools and Manufacture, 1999. 39(6): p. 885-903.
4. Thiele, J.D., et al., Effect of cutting-edge geometry and workpiece hardness on surface residual stresses in finish hard turning of AISI 52100 steel. Journal of Manufacturing Science and Engineering, 2000. 122(4): p. 642-649.
5. Lei, S., Y. Shin, and F. Incropera, Thermo-mechanical modeling of orthogonal machining process by finite element analysis. International Journal of Machine Tools and Manufacture, 1999. 39(5): p. 731-750.
6. Umbrello, D., et al., On the effectiveness of finite element simulation of orthogonal cutting with particular reference to temperature prediction. Journal of Materials Processing Technology, 2007. 189(1-3): p. 284-291.
7. Özel, T. and E. Zeren, Finite element modeling the influence of edge roundness on the stress and temperature fields induced by high-speed machining. The International Journal of Advanced Manufacturing Technology, 2007. 35(3-4): p. 255-267.
8. Komanduri, R. and Z.B. Hou, Thermal modeling of the metal cutting process—Part III: temperature rise distribution due to the combined effects of shear plane heat source and the tool–chip interface frictional heat source. International Journal of Mechanical Sciences, 2001. 43(1): p. 89-107.
9. Li, K.-M. and S.Y. Liang, Modeling of cutting forces in near dry machining under tool wear effect. International Journal of Machine Tools and Manufacture, 2007. 47(7-8): p. 1292-1301.

10. Huang, Y. and S. Liang, cutting forces modeling considering the effect of tool thermal property—application to CBN hard turning. International journal of machine tools and manufacture, 2003. 43(3): p. 307-315.
11. Shao, Y., et al., Physics-based analysis of minimum quantity lubrication grinding. International Journal of Advanced Manufacturing Technology, 2015. 79.
12. Karpat, Y. and T. Özel, Predictive analytical and thermal modeling of orthogonal cutting process—part I: predictions of tool forces, stresses, and temperature distributions. Journal of manufacturing science and engineering, 2006. 128(2): p. 435-444.
13. AOKI, H., et al., Use of alternative protein sources as substitutes for fish meal in red sea bream diets. Aquaculture Science, 1997. 45(1): p. 131-139.
14. Bocciarelli, M., G. Bolzon, and G. Maier, Parameter identification in anisotropic elastoplasticity by indentation and imprint mapping. Mechanics of Materials, 2005. 37(8): p. 855-868.
15. Nakamura, E.F., A.A. Loureiro, and A.C. Frery, Information fusion for wireless sensor networks: Methods, models, and classifications. ACM Computing Surveys (CSUR), 2007. 39(3): p. 9.
16. Delalleau, A., et al., Characterization of the mechanical properties of skin by inverse analysis combined with the indentation test. Journal of biomechanics, 2006. 39(9): p. 1603-1610.
17. Pujana, J., et al., Analysis of the inverse identification of constitutive equations applied in orthogonal cutting process. International Journal of Machine Tools and Manufacture, 2007. 47(14): p. 2153-2161.
18. Denkena, B., et al., Inverse determination of constitutive equations and cutting force modelling for complex tools using oxley's predictive machining theory. Procedia CIRP, 2015. 31: p. 405-410.
19. Chen, X., et al., Determining Al6063 constitutive model for cutting simulation by inverse identification method. The International Journal of Advanced Manufacturing Technology, 2017: p. 1-8.
20. Laakso, S.V. and E. Niemi, Using FEM simulations of cutting for evaluating the performance of different johnson cook parameter sets acquired with inverse methods. Robotics and Computer-Integrated Manufacturing, 2017. 47: p. 95-101.
21. Mirkoohi, E., P. Bocchini, and S.Y. Liang, An analytical modeling for process parameter planning in the machining of Ti-6Al-4V for force specifications using an inverse analysis. The International Journal of Advanced Manufacturing Technology, 2018: p. 1-9.
22. Sridhar, B., et al., Effect of machining parameters and heat treatment on the residual stress distribution in titanium alloy IMI-834. Journal of Materials Processing Technology, 2003. 139(1-3): p. 628-634.
23. Komanduri, R. and Z.B. Hou, Thermal modeling of the metal cutting process: Part I—Temperature rise distribution due to shear plane heat source. International Journal of Mechanical Sciences, 2000. 42(9): p. 1715-1752.
24. Lin, Z.-C., Y.-Y. Lin, and C. Liu, Effect of thermal load and mechanical load on the residual stress of a machined workpiece. International Journal of Mechanical Sciences, 1991. 33(4): p. 263-278.
25. Trigger, K., An analytical evaluation of metal-cutting temperatures. Trans. ASME, 1951. 73: p. 57.
26. Oxley, P.L.B., The Mechanics of Machining: An Analytical Approach to Assesing Machinability. 1989: Ellis Horwood.
27. Waldorf, D.J., R.E. DeVor, and S.G. Kapoor, A slip-line field for ploughing during orthogonal cutting. Journal of Manufacturing Science and Engineering, 1998. 120(4): p. 693-699.
28. Sekhon, G. and J. Chenot, Numerical simulation of continuous chip formation during non-steady orthogonal cutting. Engineering computations, 1993. 10(1): p. 31-48.
29. Waldorf, D.J., A simplified model for ploughing forces in turning. Journal of manufacturing processes, 2006. 8(2): p. 76-82.