Int J Adv Manuf Technol (2015) 78:1265–1273
DOI 10.1007/s00170-014-6739-x

ORIGINAL ARTICLE

Adaptive control for multistage machining process scenario—bar turning with varying material properties

Parikshit Mehta · Laine Mears

Received: 8 October 2014 / Accepted: 18 December 2014 / Published online: 7 January 2015

Abstract This paper discusses the multistage manufacturing scenario in context of progressive machining and demonstrates an adaptive control scheme for turning operation of a partially hardened bar. A nonlinear mechanistic force model-based control framework attempts to control the cutting force at a designated set point, with material properties changing over the cut. The force coefficients for the material are calculated offline using experimental data and Bayesian inference methods. Since the hardened part of the bar will shift the force coefficient values, an online estimation strategy (Bayesian recursive least square estimator) is used to learn the new coefficients as well as satisfying the control objective. With the newly learned coefficients passed downstream, the subsequent operation experiences no compromise of control objective as well as reduces the maximum values of force encountered. Numerical analyses presented show the adaptation and control scheme performance. Finally, the experimental analysis show the open-loop and closed-loop model adaptation and effective force set point regulation using experimental apparatus and partially hardened MS (AISI1045) bar.

Keywords Multistage machining · Mechanistic force model · Cutting force adaptive control · Bayesian estimation · Online identification of model parameters

P. Mehta (✉)
Mechanical Engineering Department, Clemson University, Clemson, SC, USA
e-mail: pariksm@clemson.edu

L. Mears
Automotive Engineering Department, CU-ICAR, Clemson University, Greenville, SC, USA

1 Machining and manufacturing process control—profitability to machining performance

Today's manufacturing industry encompasses of factory floor that is highly data integrated and involves a variety of machines connected via complex product flow path. The product customization requires production flexibility as well as demands control adaptability. In machining process control, traditional work has been focused on a single machine-single machining pass control on process variables (force/tool wear) [1–3] and on geometric features of the product [4, 5]. In prior art, the material models were calculated offline and used for model-based control, but in reality, workpiece material property can vary. So, control algorithm has to be adaptive to account for these changes. At the same time, the variation in workpiece material property is also indicative of the material quality—this knowledge can be useful in tracking product quality. This paper attempts to answer some of these issues by extending the process control from one machine to multiple machines and how knowledge generated by the process can be passed on to the next process when the input material quality is variable.

Modeling and simulation and process control are identified as the technological driving factors toward future of the manufacturing technology [6]. This requires concurrent efforts in machining process modeling, process control, machine tool programming protocol, and supporting information and communication technologies. The goal of process control is improved profitability, which must in turn be related to machining performance, i.e., the optimization and control of machining parameters and states that maximize profitability. The profitability can be further broken down at various stages in manufacturing process:

1. Single operation level
2. Part machining level
3. Machining process level
4. Enterprise level

At various levels, the control objectives differ but ultimately affecting the overall profitability. One such breakdown in terms of dynamic time constants is illustrated in Fig. 1. The single operation level control encompasses machining chatter control, force and power control, surface roughness control, and tool-wear compensation as examples. The process level control examples include quality feedback within processes and enterprise level control where the maintenance of the machining tools and cost involved directly affects the profitability of the organization.

Single operation level control has been explored in great detail from a modeling and control point of view. Starting from the earliest work by Koren [3, 2], Ulsoy [1, 7], and Mesory [8] to the recent work from Landers [9], Park and Kim [10], and Harder [11], the central theme of machining process control has mostly been on machining force control, involving either a linear or nonlinear force mechanistic model [12] and an integrator-based controller with or without adaptive algorithm to learn the model parameters. It is important to note that all these approaches have been applied to a single machine-single operation configuration.

Consider a typical manufacturing process setting which involves multiple operations on multiple machines as shown in Fig. 2. Three machines (A, B, and C) sequentially process parts 1, 2, and 3. Machines A and B perform two rough machining (stock removal) passes and machine C performs a finishing operation. The process level controller in the first operation aimed to learn and update the process model and pass on that information to the second machine.

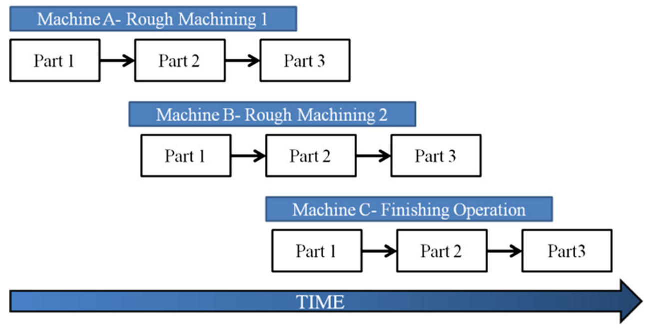


Fig. 2 System information routes in a typical manufacturing process

Such control architecture not only promises the production and part quality control but also has potential to perform long term monitoring of the part and process variables involved. Execution of such architecture requires highly integrated machine shop floor, open architecture control (OAC), and intelligent control schemes. As a demonstration of what such control architecture could achieve, we present a demonstrative case by controlling cutting force during bar turning when bar material properties are not constant throughout the cut length.

2 Demonstrative machining application: bar turning with varying material properties

Consider a simple bar turning operation done on a computer numerical controlled (CNC) lathe (Fig. 3). In the manufacturing process setting discussed earlier, this represents machine A. Because of the prior model development, the force control

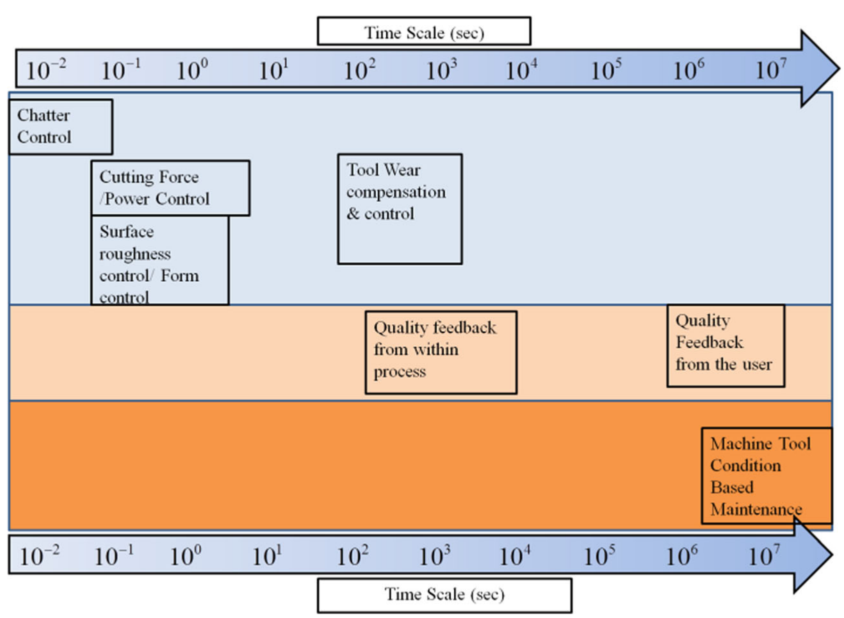


Fig. 1 Time scales in optimization and control of profitability components

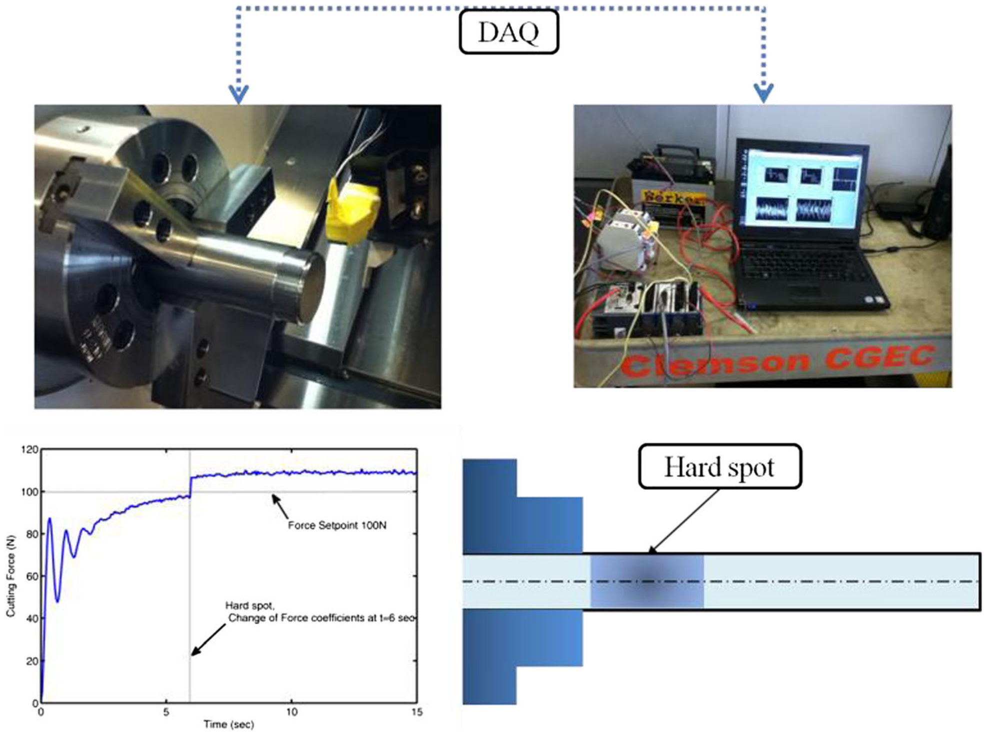


Fig. 3 Bar turning with hard spot in input material

algorithm attempts to control the cutting force at 100 N. Suppose the input material quality variation results in a hard spot, encountered in the 6th second of the cut. The change in material coefficients is not registered by the control algorithm, which results in incorrect set point tracking as shown in inset plot of Fig. 3.

Suppose this information on material property change was available at the start of the cut in a model-based control process, the force control algorithm would have successfully satisfied the control objective despite of the change in material hardness. Referring to Fig. 4, the same control set point and material parameters have been simulated, this time with prior knowledge of the material property change. The cutting force is controlled at 100 N, with the exception of some transience at the point the change in hardness.

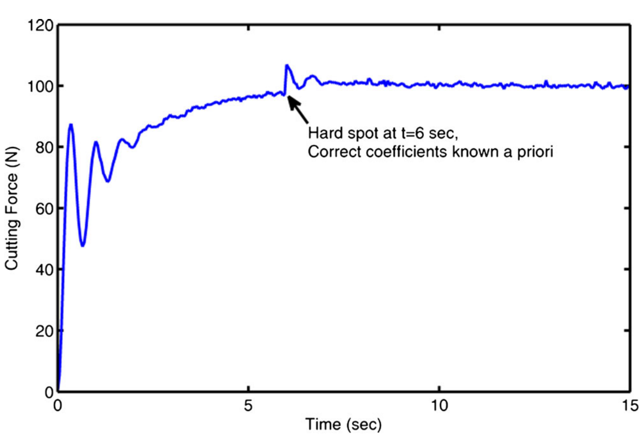


Fig. 4 Bar turning with hard spot with a priori known coefficients

To accomplish the process control as discussed in the previous section for the bar turning operation, the requirements are as follows:

- Accurate process model form and parameter values,
- In-process parameter value update algorithm while continuing to satisfy the control objective, and
- Parameter learning and transfer of this knowledge to next operation/machine.

To that end, the remainder of this paper discusses the Bayesian inference technique for mechanistic force model, estimation scheme for the force coefficient parameters, and numerical analysis of the effect of a priori knowledge of the force coefficients.

2.1 Nonlinear mechanistic machining force model identification with Bayesian inference

The effectiveness of a model-based control algorithm depends upon the validity of the model. The linear mechanistic force model is ineffective for large ranges of feeds and speeds. Therefore, an alternate force model is investigated, which is given as follows [7, 12]:

$$F = K_1 b h^{K_2} \tag{1}$$

where K_1 and K_2 are empirical constants that relate to material property and tool workpiece interaction mechanisms, b

is the depth of cut, and h is feed per revolution of the work-piece (in the case of turning). The force estimated thus is the average force over the revolution of the workpiece. The identification of the coefficients was performed using Bayesian inference techniques. Expressing the uncertainty in terms of probability distributions, and using the Bayes theorem [13, 14], the posterior beliefs in the value of force coefficient can be expressed as the following:

$$p\left(K_1, K_2 \middle| F\right) \propto p\left(F \middle| K_1, K_2\right) p(K_1, K_2) \tag{2}$$

Here, $p(F|K_1,K_2)$ represents the data likelihood and $p(K_1, K_2)$ is the prior distribution of the force coefficients. Figure 5 shows the prior $p(K_1,K_2)$ and posterior $p(K_1,K_2|F)$ the after seven updates.

It is evident from Fig. 5 that though the initial belief in the force coefficient value is far from the true coefficients, few updates are sufficient to identify the correct values. Every time the update is made, the variance of the force coefficient distribution reduces. The detailed Bayesian inference procedure applied to machining model identification has been reported in [15] by the authors. To identify the coefficients offline, the experimental data is required, with which the model shown in Eq. (1) can be fitted. Such an experimental data set is shown in Table 1. This data was obtained cutting Ti-Al-64V (grade 5 titanium) alloy with uncoated carbide tools (with depth of cut of 1.5 mm). The cutting and feed forces were measured using a strain gauge-based force sensor. The values shown in the table refer to the average cutting force over the length of the cut. For every data obtained, a new cutting edge was deployed; all the cuts are taken in dry (no coolant) conditions.

The Bayesian inference scheme used here updates the belief in the force coefficients with the prior provided as [1100, 0.5]. The estimation scheme sequentially updates the belief in the coefficient values as new experimental data is obtained. Figure 6 shows updated beliefs in the coefficient values; after seven updates, the estimated coefficient values converge to the true values of coefficients.

Table 1 Experimental data used to perform Bayesian inference of force coefficients

Test ID	Feed (mm/rev)	Cutting speed (m/min)	Cutting force (N)	Feed force (N)
test88	0.05	75	206	199
test89	0.05	120	206	191
test91	0.15	75	480	302
test92	0.15	120	470	310
test94	0.25	75	702	360
test95	0.25	120	674	418
test96	0.05	165	224	234
test97	0.15	165	470	360

With converged coefficient values, the measured values of forces are compared with the predicted force values as shown in Fig. 7. The purpose of doing Bayesian inference on the experimental data is to demonstrate the use of inference technique applied to a nonlinear mechanistic force model. The same technique may be extended to perform online identification of parameters, which is discussed in next section.

2.2 Machining force model online (in-process) recursive identification

A typical machining force control block diagram is shown in Fig. 8, where the force is controlled by controlling the feedrate override control. For most of the force control applications, feedrate control is chosen over depth of cut controls as seen in [3, 7, 10, 12, 16]. For successful control of the cutting force,

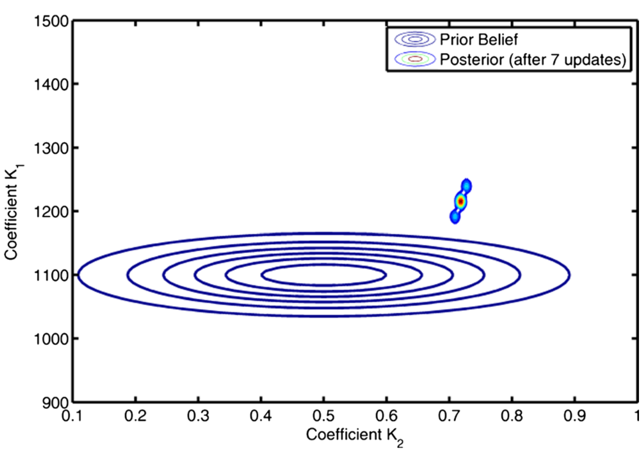


Fig. 5 Joint probability distribution contours for coefficient values: prior and posterior

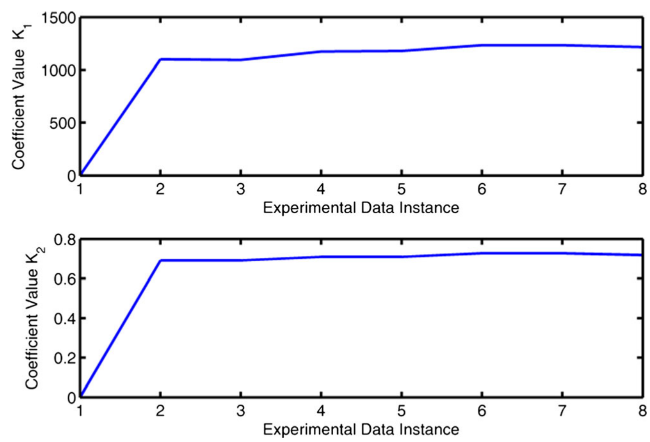


Fig. 6 Sequential estimation of nonlinear mechanistic force model coefficients

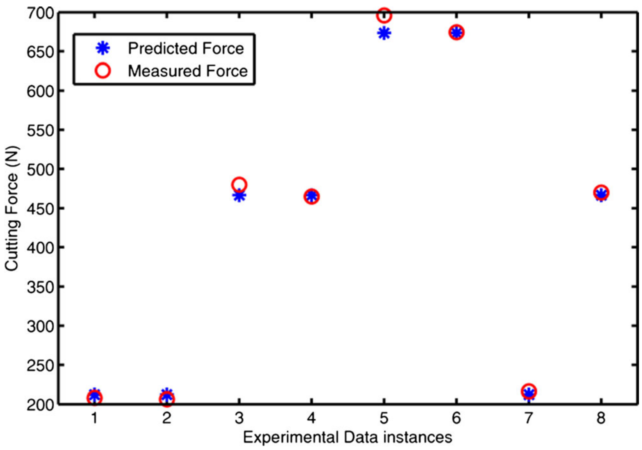


Fig. 7 Bayesian inference of the nonlinear force model

the force model should be known with reasonable accuracy. With this model, the force set point is converted to feed set point; the feedrate is controlled with a PI controller in a closed loop. The controlled feedrate is then applied to machining process, with cutting force measured with help of a strain gauge-based force sensor. From measured force, the coefficients can be estimated. In the context presented, it is imperative to identify the correct coefficients to be able to transfer them to the next machine on machining line. Closed loop identification of the parameter estimate requires inclusion of the control law in the identification procedure [17].

To estimate the force coefficients, a recursive least square (RLS) estimation technique is traditionally applied [17]. RLS estimation is a special case of Bayesian parameter estimation (fixed but unknown parameters) method with linear model and uncertainty of Gaussian nature [18]. This requires log linearization of the nonlinear mechanistic force model. The log-linearized force model can be expressed as

$$y(k) = \ln\left(\frac{F}{b}\right) = \Phi(k)\theta^T(k) \tag{3}$$

where $\Phi(k) = [1 \quad \ln h]$ and $\theta(k) = [\ln K_1 \quad K_2]$; this way the nonlinear mechanistic force model coefficients can be identified with the recursive least square estimator. The estimation scheme can be expressed using the following set of equations:

$$\begin{aligned}\theta(k+1) &= \theta(k) + L(k)[y(k+1) - \Phi(k+1)\theta(k)]\\ L(k) &= \frac{P(k)\Phi(k+1)}{\lambda + \Phi^T(k+1)P(k)\Phi(k+1)}\\ P(k+1) &= \frac{P(k) - L(k)\Phi^T(k+1)P(k)}{\lambda}\end{aligned} \tag{4}$$

The set of equations presented in Eq. (4) shows the recursive least square estimation of parameter vector $\theta(k)$, $L(k)$ is called optimal gain matrix, and $P(k)$ is called the estimation-error covariance [19]. Optimal gain matrix determines the amount by which the parameter estimate adjusts as new observation is obtained, and estimation error covariance refers to uncertainty in the value of parameter estimate. The forgetting factor was chosen to be $\lambda=0.995$ for the simulation presented in this work. This algorithm works well in case the parameters being estimated do not vary with time. Particular case at hand requires dynamic estimation of parameters. To accomplish this, the parameter estimation vector is now presented as a random walk system [17].

$$\begin{aligned}\theta(k+1) &= \theta(k) + w(k)\\ y(k) &= \Phi(k)\theta^T(k) + r(k)\end{aligned} \tag{5}$$

In Eq. (5), $w(k)$ is Gaussian distribution-sampled noise parameter with covariance matrix $P_1(k)$ and $r(k)$ is Gaussian distribution-sampled noise parameter (indicating measurement error) with covariance matrix $P_2(k)$. With these new definitions, the Bayesian recursive parameter estimation scheme can be described using the following equations:

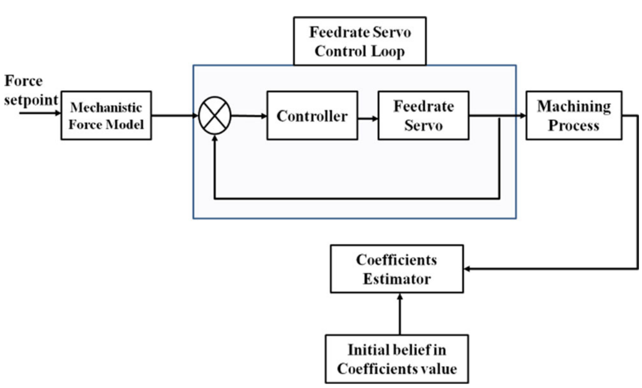


Fig. 8 Block diagram of control loop and adaptation scheme

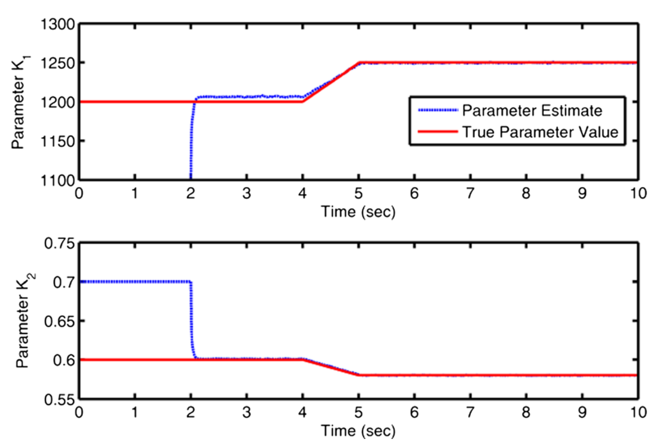


Fig. 9 Identification of force coefficients in response to change in material hardness

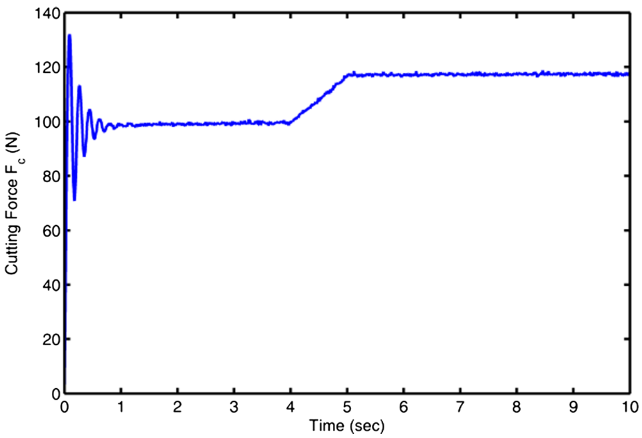


Fig. 10 Cutting force trajectory (set point 100 N)

$$\begin{aligned}\theta(k+1) &= \theta(k) + L(k)[y(k+1) - \Phi(k+1)\theta(k)] \\ L(k) &= \frac{P(k)\Phi(k+1)}{P_1(k) + \Phi^T(k+1)P(k)\Phi(k+1)} \\ P(k+1) &= P(k) - L(k)\Phi^T(k+1)P(k) + P_2(k)\end{aligned} \tag{6}$$

In Eq. (6), the covariance matrices defined earlier help the gain matrix $L(k)$ not get impoverished when the estimation error vanishes and helps track the coefficient values efficiently.

3 Numerical simulations

As discussed in the introduction, the basic idea is to learn the model parameters and track them as they change with respect to time. In the context of turning a bar, the case study is presented in which the force coefficients change because of change in hardness of the material. For numerical simulation, the block diagram shown in Fig. 8 was implemented in Matlab Simulink along with online Bayesian RLS identification scheme. The objective is to control force at 100 N, with depth of cut to be 2 mm. At time t=4 s, the machining force coefficients change as the material hardness changes. At the start of the cut, the coefficient values are [1200;0.6], and at t=4, the values change to [1250;0.58]. The goal of estimation scheme is to identify these changes in the force coefficient as quickly as possible to drive the cutting force to the required set point. The result of these simulations is shown in following figures.

In Fig. 9, the RLS scheme quickly converges to the true coefficient values. Figure 10 shows the force trajectory with respect to time. As the cut starts, because of false initial guess ([1100;0.7]), the force value does not converge to set point value of 100 N. The identification algorithm starts at t=2 s. The RLS scheme quickly adapts to the parameters values of [1200;0.6]. At t=4, the parameter values again change to [1250;0.58]. Note that because of open loop estimation, the new parameter values are still not fed to the controller in order to achieve the set point necessary; that is the reason why in Fig. 10, after the hardness change in material, the set point is shifted at about 120 N.

4 Experimental analysis

For the experimental validation of this process control scheme, refer to the current experimental setup as shown in Fig. 11. An Okuma-LB4000EX CNC lathe is instrumented with a custom 2 directional strain gauge-based force sensor that measures cutting force and feed force. The strain gauges

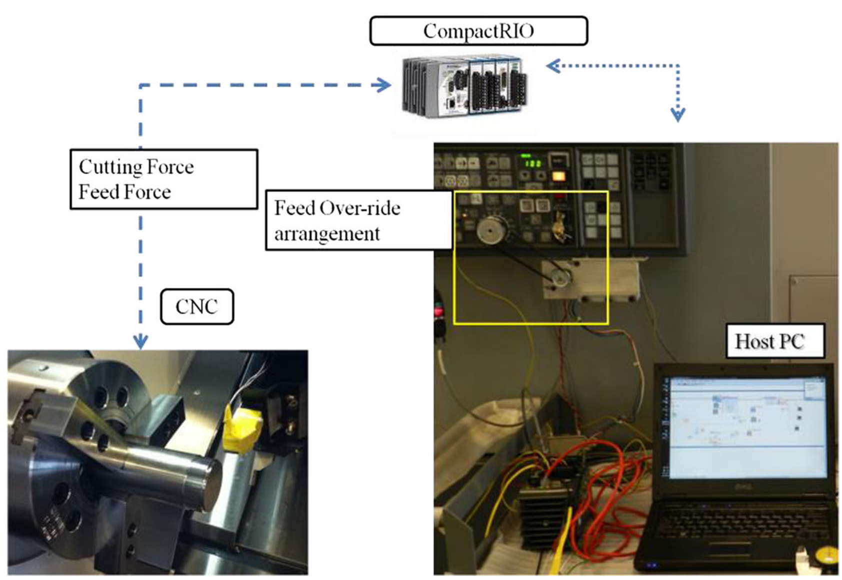


Fig. 11 Experimental set up for feed-override control

Fig. 12 Experimental verification of the hardened bar cutting force control: AISI1045 steel bars hardened to 45 HRC in partial length

are powered by two charge amplifiers with in-built analog filters. The data acquisition is performed using National Instruments CompactRIO hardware and National Instruments LabVIEW software. For controlling the feedrate of this CNC, a PMDC servomotor-powered pulley drives the feed-override knob on the CNC machine panel.

The PI controller, coefficient estimation, and monitoring algorithm will be implemented in the LabVIEW software. Based on the initial tests, the feedrate override control has proven to be working for the constant force control applications.

For the experimental verification of the scheme, first it is important to observe how cutting force gets affected by change in material hardness. In the experimental analysis, an AISI1045 1.5-in.-diameter steel bar was induction hardened to 45 HRC in partial length shown in Fig. 12. The pattern includes 2-in. regions of hardened part symmetrically placed from the centerline of the length of the bar. Since in reality, the transition from non-hardened region to hardened region will be smooth, and it was also reflected in numerical simulations.

4.1 Open loop estimation

Using the experimental setup described in previous section, the constant depth of cut (2 mm), constant feed (0.1 mm/rev), and constant speed (200 RPM), the data was taken for the 5-in. length of the pattern 1 bar, and this is shown in Fig. 13.

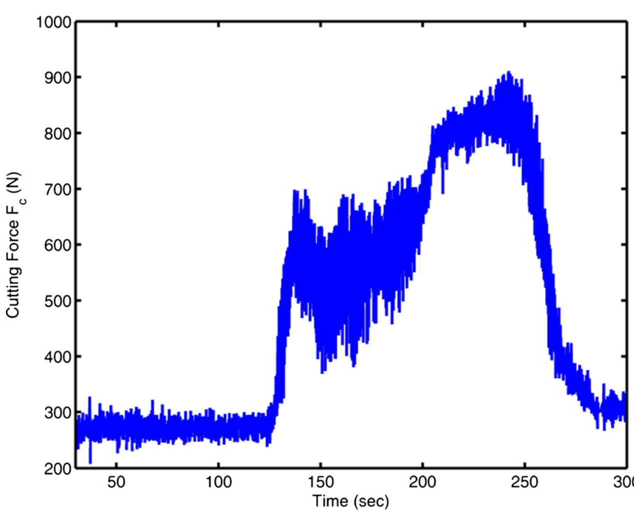


Fig. 13 Cutting force trajectory for the hardened bar—cutting force rises when tool encounters the hardened part of the bar; the trajectory of the force then is representative of the material hardness encountered

As it can be observed, the cutting force trajectory diverges once it encounters the hardened part of the bar. It also seems to enter a chatter region which is characterized by large amplitude vibrations of the force. The force and feed data was processed to identify the process parameters using exponentially weighted recursive least squares (E-RLS) and Bayesian recursive least square (BRLS) shown in Fig. 14.

The identified parameters, when fedback to the input data to predict the force output (offline—post process), are shown in Fig. 15.

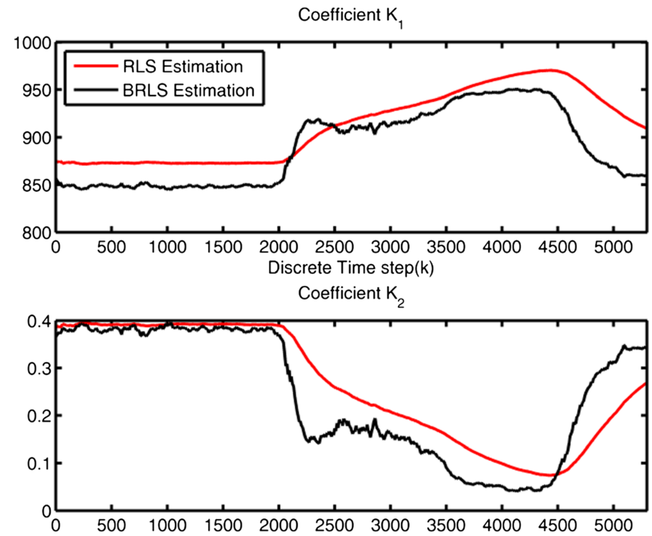


Fig. 14 Identified parameters for hardened bar machining data

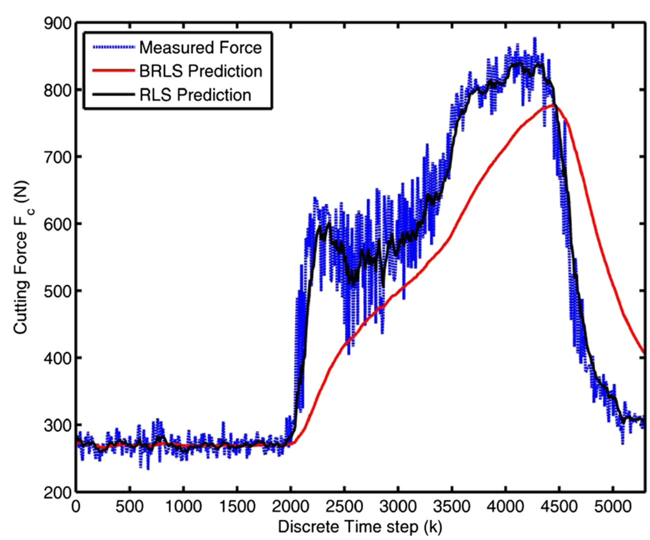


Fig. 15 Force prediction using identified parameters—comparison between recursive least square and Bayesian recursive least square approaches (200 RPM, 0.1 mm/rev feed, 2-mm depth of cut)

As it can be seen from Fig. 15, the cutting force model parameters are predicted accurately using the Bayesian recursive least square method (Kalman filter), which in turn, produces the cutting force values. Note that this discusses the open loop estimation of the force model coefficients, which results in cutting force not regulated at a constant value. The force value increasing despite of the same feed and depth of cut suggests the material property change. If the force value regulation is desired, the estimation of the force coefficients need to happen online (in closed loop), which is discussed in the following section along with experimental data.

4.2 Closed loop estimation

The estimation of the machining force coefficient can be performed in closed loop following the adaptive control structure presented in this work. The experimental implementation was done in the structure shown in Fig. 16. The feedrate servo controller sampling rate is 1 ms (1000 Hz), while parameter estimator scheme is implemented at minimum to 200 to 500 ms.

Experiments for the closed loop control with estimation were performed for AISI 1045 material; the results are shown in Fig. 17 along with model coefficient estimated values. The coefficient values assume nonzero values after about 100 s into the cut; this is because the estimator was turned on after cutting tool was cutting the metal. This was done to prevent the estimator to produce unstable values (NaN—not a number values). As it can be observed from the plot, the closed loop estimation of the model parameters ensures force set point regulation in spite of hitting the hard spot in the workpiece.

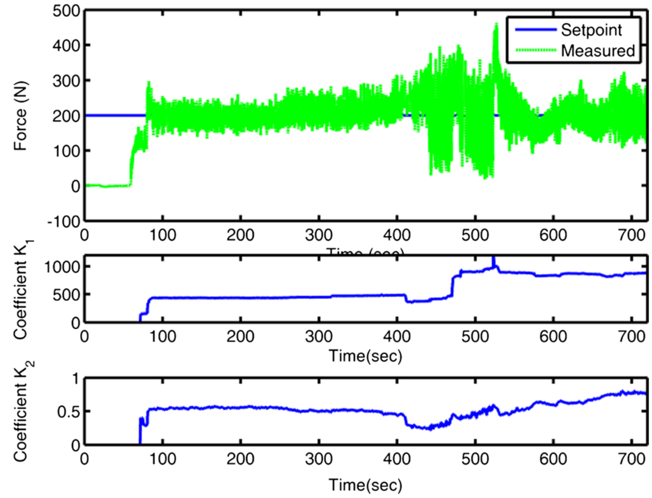
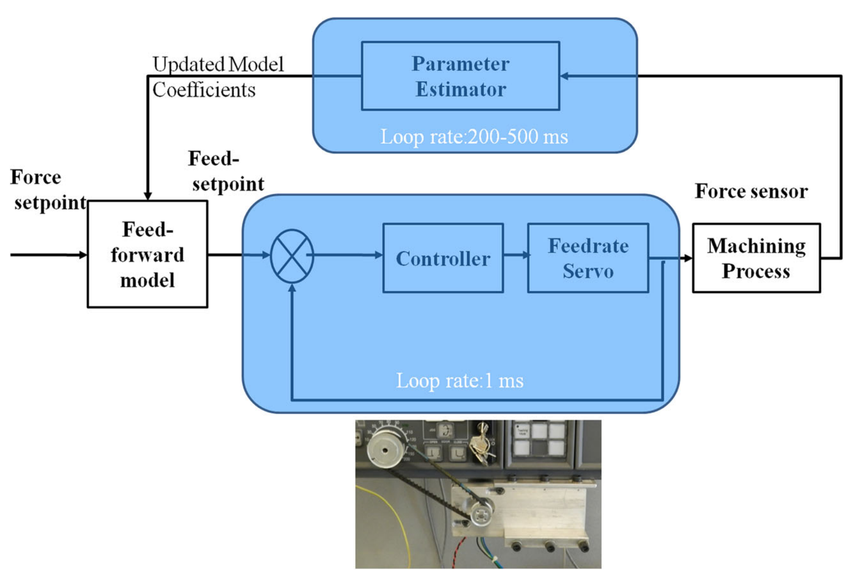


Fig. 17 On-line estimation of force coefficients along with set point regulation (200 RPM, 0.05 mm/rev nominal feedrate and force control set point of 200 N)

5 Conclusion

Machining process control has been investigated in theory and application for decades but has seldom been implemented on industrial systems for various reasons. Primarily the closed architecture legacy controllers prohibit access to the servo motor control signals for implementing intelligent controllers. Also, the integration of the external sensors (for force, power, and surface roughness measurements) directly to the machine controller has been difficult. Recently, advances in open architecture control (OAC) have opened these opportunities and CNC machines on the shop floor are connected through TCP/IP communication protocols which are also explored for condition-based monitoring (CBM) of machine tools [20]. All these concurrent development in machine tool software

Fig. 16 Implementation of adaptive control scheme on experimental setup



and hardware are leading toward more and more use of intelligent controllers toward efficient machining.

This work discussed a perspective in-process level control in which the input material variation is registered in terms of force coefficients and information is passed on to the next machine in the line. This was accomplished with linearization of the nonlinear mechanistic model and using the recursive least square estimator. This is a concept demonstration that can be expanded further in terms of quality prediction over multiple parts, tool wear monitoring, and general health monitoring of multistage machining process.

Acknowledgments The authors wish to thank the National Science Foundation for the support of this work under Grant No. 0954318. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the National Science Foundation.

References

1. Ulsoy GA, Koren Y (1993) Control of machining process. J Dyn Syst Meas Control 115:301–308
2. Koren Y (1983) Computer control of manufacturing systems. McGraw Hill Book Company.
3. Koren Y (1988) Adaptive control systems for machining. In American control conference.
4. Benardos P, Mosialos S, Vosniakos G (2006) Prediction of workpiece elastic deflections under cutting forces in turning. Robot Comput Integr Manuf 22:505–514
5. Mehta P, Mears L (2011) Model based prediction and control of machining deflection error in turning slender bars. In international manufacturing science and engineering conference, Corvallis
6. O'Sullivan E (2011) A review of international approaches to manufacturing research. Cambridge.
7. Landers R, Ulsoy A, Ma Y (2004) A comparison of model-based machining force control approaches. Int J Mach Tools Manuf 44: 733–748
8. Masory O, Koren Y (1983) Variable gain adaptive control system for turning. J Manuf Syst 2(2):165–173
9. Landers R, Ulsoy G (2000) Model-based machining force control. J Dyn Syst Meas Control 122:521–527
10. Park Y, Kim T, Woo J, Shin D, Kim J (1998) Sliding mode cutting force regulator for turning process. Int J Mach Tools Manuf 38:911–930
11. Harder L, Iaaksson A (1997) Force control in turning based on robust PI controller design. J Eng Manuf 211:165–175
12. Elvestawi MA (1987) Parameter adaptive control in peripheral milling. Int J Mach Tools Manuf 27(3):399–414
13. Wilson SP, Dahyot R, Cunningham P (2008) Introduction to Bayesian methods and decision theory. In maching learning techniques for multimedia. Springer, pp. 3–19.
14. Tipping M (2003) Bayesian inference: an introduction to principles and practices in machine learning.
15. Mehta P, Kuttolamadom M, Mears L (2012) Machining process power monitoring: Bayesian update of machining power model. In proceedings of seventh annual international manufacturing science and engineering conference. Notre Dame.
16. Qin Y, Park S (2005) Robust adaptive control of machining operations. In Proceedings of IEEE international conference on mechatronics and automation. Niagara Falls.
17. Ljung L (1999) System identification—theory for the user. Prentice-Hall.
18. Chatterjee S, Alam S, Mishra R (2009) Sequential Bayesian technique: an alternative approach for software reliability estimation. Sadhana 34(2):235–241
19. Simon D (2006) Optimal state estimation, Willey.
20. Mehta P, Werner A; Mears L (2013) Condition based maintenance-systems integration and intelligence using naive Bayesian classification and sensor fusion. J Intell Manuf.