Rapid parameter estimation of CNC feed drive systems

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ABSTRACT

As Industry 4.0 evolves with the abundance of data, networking capabilities and new computing technologies, manufacturers are looking for ways to exploit this revolution. The demands of machine tools and their feed drive systems require manufacturers to optimally plan and schedule maintenance actions to minimize costs. These actions can be supplemented by capitalizing on machine data and the idea of cyber-physical systems, with the use of edge and cloud computing, by monitoring important machine characteristics. A substantial benefit to manufacturers would be the ability to monitor the health characteristics of machine tools to aid them in their maintenance planning. Some of the challenges manufacturers face with this are the computing time and effort needed to analyze and evaluate the vast amount of machine data available. A step towards real-time condition monitoring of machine characteristics includes rapid parameter estimation of CNC machine tool systems. The estimation of mass and friction allow for the monitoring of CNC feed drive health. This work proposes the estimation of such parameters from real-world industrial machine tool data. A Feed drive testing procedure is developed for smart data acquisition. Data analysis and recursive least squares methods are used to extract key parameters representative of machine health that are realizable on edge computing devices.

Keywords: Condition monitoring, parameter estimation, machine tool, feed drive, maintenance, Industry 4.0

1. INTRODUCTION

The manufacturing industry is moving towards the digitalization and networking of factories due to the demands for increased quality, efficiency, and minimizing costs. The maintenance costs of industrial machines is of great interest to manufacturers. One method in minimizing maintenance costs is to optimize the scheduling and planning of maintenance activities. In the machine tool industry, this includes planning when to maintain, repair, or replace machine tool systems and components. With the digital age of manufacturing, there exists an abundance of machine data that is representative of machine tool health. With the correct analysis, this data can aid maintenance personnel in minimizing maintenance related costs.

The core components of many machine tools, and often the most expensive to maintain, are the feed drives used to position the tool and/or workpiece. Generally, feed drive systems contain ball screws, linear guideways, gear reducers, and drive motors (typically AC servo motors). Feed drive monitoring has been reviewed by several researchers.[1–5] However, there is a need for rapid parameter estimation techniques to characterize machine tool feed drives and monitor their condition over time.

Parameters such as mass and friction can be used to monitor the health of a feed drive. As a machine axis wears, the wear is reflected in the friction dynamics. Identifying and tracking the level of friction over time can thus be beneficial to manufacturers. Such identification is made possible through the data captured by machine tool numerical controllers (NCs) and includes measured positions and drive torque/current. The proposed method utilizes axis positions and the motor drive current to estimate feed drive mass and friction through recursive least squares (RLS) as presented by Ref. 6. The identification of feed drive mass allows for the simulation of the feed drive dynamics

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The identification of friction parameters in feed drive systems has been investigated in the literature.[6–14] Likewise mass/inertia identification has also been investigated.[6,8,11,15] Several of these methods only consider experimental setups that are not indicative of real machine tools. Other methods also require the analysis of frequency-domain characteristics which may require offline data analysis.

2. METHODOLOGY

The methods in this work include the derivation of a feed drive model which is converted to a parametric form for recursive least squares (RLS) estimation. Feed drive test procedures are then used to measure the relevant data required for parameter estimation.

2.1 Feed Drive Model

Estimating the parameters of a ball screw feed drive axis requires a model that can be converted into a linear parametric form. Such a form includes the effects of inertia, friction dynamics, and the drive force. Therefore, a linear axis can be modelled by

$$M\ddot{x} = F_d - F_f \tag{1}$$

where M is the mass, x is the axis position, F_d is the drive force provided by the motor, and F_f is the friction force. If the input current to the motor is known, then the drive force can be calculated as

$$F_d = \frac{K_t i_d}{R} \tag{2}$$

where K_t is the motor torque constant, i_d is the drive current, and $R = l/2\pi$ is the transmission ratio of the drive with l being the lead of the ball screw. The friction effects observed in linear machine axes can be modelled by viscous, Coulomb, and Stribeck friction as follows:

$$F_f = B\dot{x} + F_C \operatorname{sgn}(\dot{x}) + (F_B - F_C)\operatorname{sgn}(\dot{x})e^{-\frac{|\dot{x}|}{v_s}}. \tag{3}$$

Here, B is the viscous friction coefficient, F_C is the Coulomb friction, F_B is the breakaway friction, and v_s is the Stribeck velocity. Combining equations (1), (2), and (3), the axis dynamics are modelled as

$$M\ddot{x} = \frac{K_t i_d}{R} - \left(B\dot{x} + F_C \operatorname{sgn}(\dot{x}) + (F_B - F_C)\operatorname{sgn}(\dot{x})e^{-\frac{|\dot{x}|}{v_s}}\right). \tag{4}$$

2.2 Parameter Estimation Method

The identification method follows that of Ref. 6 where recursive least squares (RLS) is used to identify the mass and friction parameters of the feed drive. The identification method follows two steps: (1) the mass, viscous coefficient, and the Coulomb friction are first estimated and (2) the breakaway friction and Stribeck velocity are identified thereafter. This method is followed as Stribeck behavior is generally a low-velocity phenomenon. Thus, the second step in the identification method is performed on low-velocity waveform data.

RLS attempts to minimize a cost function of the response variable, regressor data, and the model parameters. Using the parametric form in equation (5) where y is the response data, ϕ is the regressor data, and θ are the model parameters,

$$y(k) = \phi^T(k)\theta(k), \tag{5}$$

the cost function is defined as the sum of least squares:

$$J(\hat{\theta}, k) = \frac{1}{2}\sum_{i=1}^{k} \lambda^{k-i}\left(y(i) - \phi^T(i)\hat{\theta}(i)\right)^2. \tag{6}$$

The factor λ is the exponential forgetting factor. The recursive solution that minimizes the cost function (6) is

$$\hat{\theta}(k) = \hat{\theta}(k-1) + L(k)\left(y(k) - \phi^T(k)\hat{\theta}(k-1)\right) \tag{7}$$

where the gain vector L and the covariance matrix P are given as

$$L(k) = \frac{P(k-1)\phi(k)}{\lambda I + \phi^T P(k-1)\phi(k)} \tag{8}$$

and

$$P(k) = \left(I - L(k)\phi^T(k)\right)\frac{P(k-1)}{\lambda}. \tag{9}$$

To identify the mass, viscous coefficient, and the Coulomb friction, the feed drive model in equation (1) is altered to exclude the effects of Stribeck friction and rearranged for the drive force or current:

$$\frac{K_t i_d}{R} = M\ddot{x} + B\dot{x} + F_C \operatorname{sgn}(\dot{x}). \tag{10}$$

The parametric model is then

$$y = \phi^T\theta = \begin{pmatrix}\ddot{x} & \dot{x} & \operatorname{sgn}(\dot{x})\end{pmatrix}\begin{pmatrix}M \\ B \\ F_C\end{pmatrix} \tag{11}$$

where $y = K_t i_d/R$ and the linear velocity $\dot{x}$ and acceleration $\ddot{x}$ are calculated via discrete differentiation.

To identify the breakaway friction and Stribeck velocity, first the Stribeck friction is estimated using the identified mass, viscous coefficient, and Coulomb friction by

$$F_{Stri} = \frac{K_t i_d}{R} - \hat{M}\ddot{x} - \hat{B}\dot{x} - \hat{F}_C \operatorname{sgn}(\dot{x}). \tag{12}$$

Next, the Stribeck friction relationship is linearized by taking the natural logarithm,

$$\ln|F_{Stri}| = \ln|F_S - F_C| - \frac{|\dot{x}|}{v_s} \tag{13}$$

which forms the basis for the following parametric form:

$$y = \phi^T\theta = \begin{pmatrix}1 & |\dot{x}|\end{pmatrix}\begin{pmatrix}\ln|F_S - F_C| \\ -\frac{1}{v_s}\end{pmatrix} \tag{14}$$

where $y = \ln|F_{Stri}|$ where F_{Stri} is given in equation (12).

2.3 Feed Drive Test Procedure

The axis test is comprised of a constant velocity reference trajectory performed at various locations along the axis. The constant velocity waveform includes passes at increasing velocities so the effects of Stribeck friction become negligible. The waveforms cover a distance of 30 mm and oscillate at velocities increases from 1250 mm/s to about 9350 mm/s. See Fig. 1 for the reference position trajectory. This work focused on the section of the test data that oscillates about the position at −300 mm as shown in Fig. 2.

3. EXPERIMENTS AND RESULTS

3.1 Experimental Setup

Machine axis tests were performed on a Grob G515 machining center used in manufacturing processes. The axis under consideration was the x-axis which consists of a ball screw driven by an AC servo motor controlled by a Siemens SINUMERIK 840D NC. This controller uses a cascaded proportional-proportional-integral control structure, or P-PI control. The AC motor has a rated torque of 26.0 Nm and a rated current of 18.0 A. The measured signals include linear and angular position of the axis and the motor drive current. Linear position measurements were measured by a glass scale encoder and angular measurements via the motor's rotary encoder. The velocity and acceleration is estimated through discrete differentiation. The current measurement is determined from the NC.

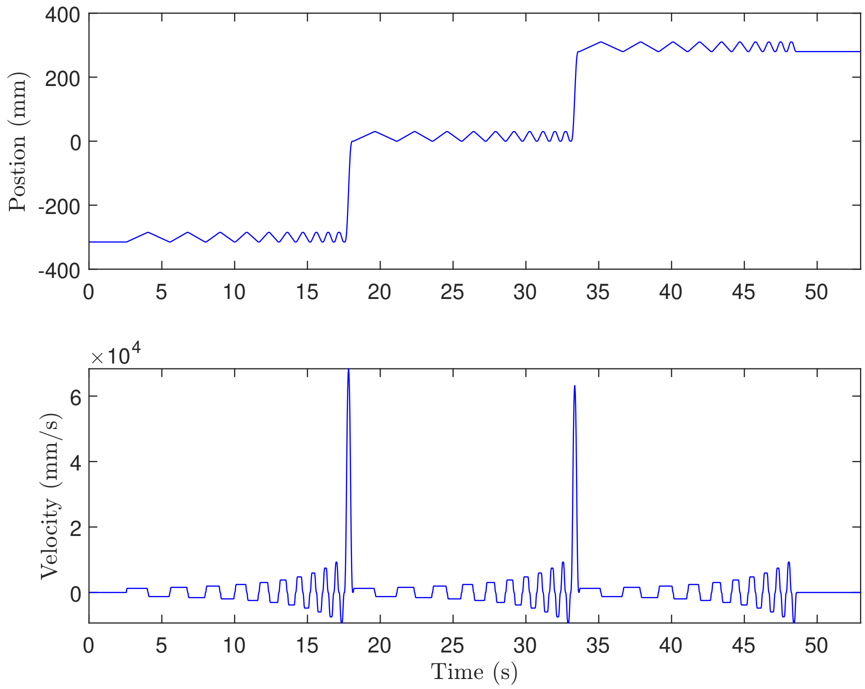

Figure 1. Constant velocity waveform used for feed drive parameter estimation.

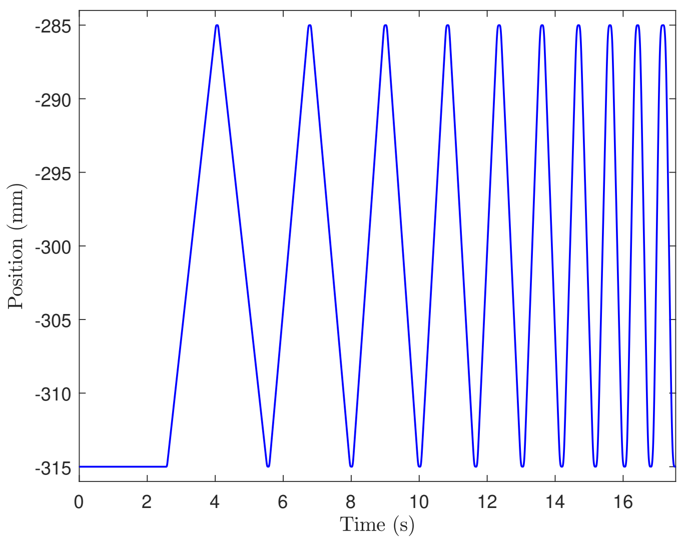

Figure 2. Constant velocity waveform at -300 mm used in this work.

3.2 Results

To estimate the feed drive mass, viscous coefficient, and Coulomb friction, RLS was applied to the waveform shown in Fig. 2. The covariance matrix and the forgetting factor were initialized to

$$P = \begin{pmatrix} 10^6 & 0 & 0 \\ 0 & 10^6 & 0 \\ 0 & 0 & 10^6 \end{pmatrix}$$
$$\lambda = 0.99995$$

for the estimation of the mass, viscous coefficient, and the Coulomb friction. For the Stribeck parameters, the covariance and forgetting factor were

$$P = \begin{pmatrix} 10^6 & 0 \\ 0 & 10^6 \end{pmatrix}$$
$$\lambda = 0.99995.$$

The RLS estimates of the parameters with respect to time are shown in Fig. 3. The values of the parameters were determined by taking the average of the estimates after the initial transient period ended. The parameters are listed in Table 1.

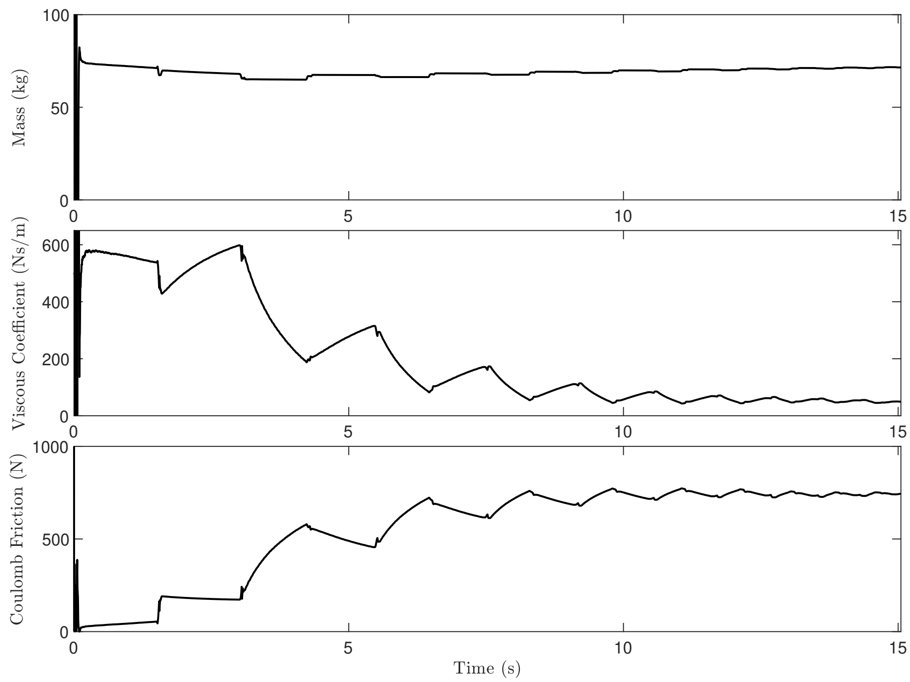

Figure 3. RLS estimates for feed drive mass, viscous friction coefficient, and Coulomb friction.

Table 1. Estimated Model Parameters

Parameter	Value	Unit
Mass, M	69.1	kg
Viscous coefficient. B	54.2	N·s/m
Coulomb friction, F_C	742.8	N

To estimate the Stribeck friction parameters, the input data was truncated at 10 seconds to exclude high-velocity data that is not relevant to the Stribeck phenomenon. The estimated parameters are shown in Fig. 4 and listed in Table 2.

The measured friction and estimated friction are plotted in Fig. 5. A mismatch between the measured friction and estimated friction is seen. The actual feed drive friction is not symmetric about the position. The CNC axis experiences higher friction under negative velocity (i.e. the axis is moving in reverse). To achieve a more accurate

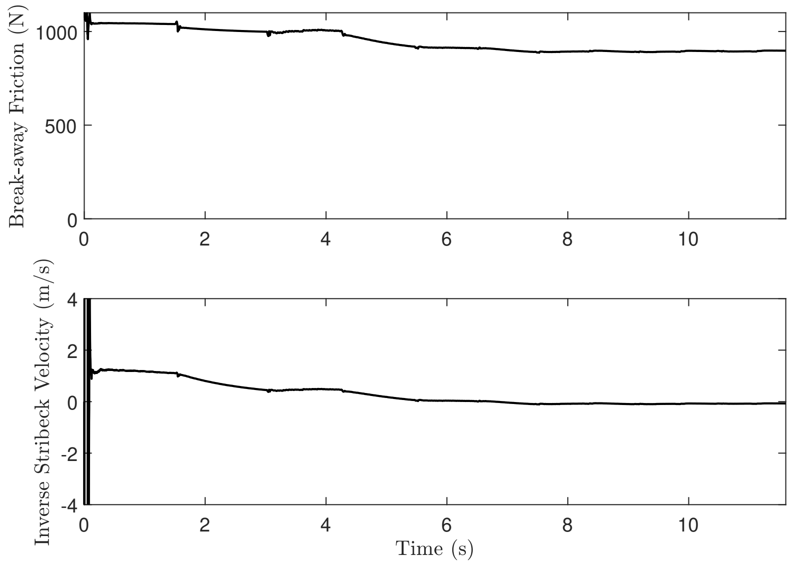

Figure 4. RLS estimates for breakaway friction and Stribeck velocity.

Table 2. Estimated Stribeck Friction Parameters

Parameter	Value	Unit
Breakaway friction, F_B	946.2	N
Stribeck velocity, v_s	0.864	m/s

friction estimate, the model must account for different Coulomb friction for the forward and reverse directions. Additionally, the Stribeck friction estimate is less pronounced than what is actually observed at lower velocities. However, the viscous friction appears to be more accurate as the slop of the estimated friction is similar to what is measured.

To validate the estimated feed drive model the position and velocity loop control gains must first be known. These gains were estimated via RLS using the following error and reference velocity for the position loop proportional gain, and the drive current and velocity error for the velocity loop proportional and integral gains (see Ref. 6). The tracking errors and modelling error were calculated for a constant velocity trajectory. The tracking error is defined as

$$e_t = x_{\mathrm{ref}} - x_{\mathrm{act}} \tag{15}$$

where x_{ref} is the reference position and x_{act} is actual position achieved either by the CNC or by the model. Likewise, the modelling error is defined as

$$e_m = x_{\mathrm{CNC}} - x \tag{16}$$

where x_{CNC} is the actual CNC feed drive position. The tracking and modelling errors are shown in Fig. 6 where the tracking error of the model and actual CNC feed drive are given. The estimated model shows comparable performance to the actual CNC. The tracking errors both increase as the velocity increases as the controller struggles to maintain the reference position. Differences may be accounted for by the discrepancy in the friction model. The mean absolute tracking errors were 1.19 mm and 1.37 mm for the model and the CNC, respectively. The model error is relatively low in magnitude with a mean absolute error of 0.18 mm.

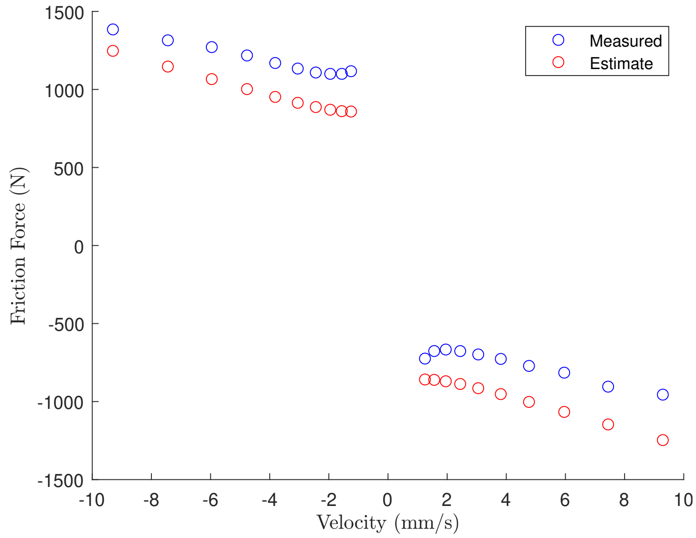

Figure 5. Measured and estimated friction forces at varying feed drive velocity.

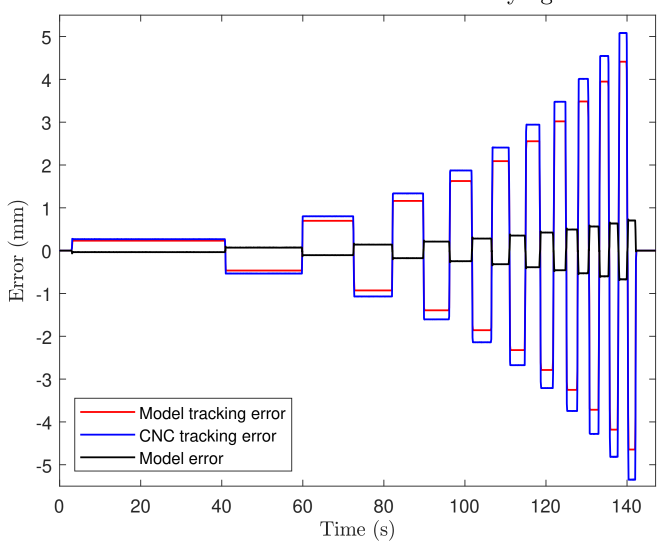

Figure 6. Tracking errors for the model and actual CNC feed drive, and the modelling error.

4. CONCLUSIONS

A method for rapid parameter estimation of an industrial CNC machining center is proposed. The method outlines a constant velocity axis test that yields the relevant data needed for RLS parameter estimation. Next the feed drive mass, viscous friction coefficient, and Coulomb friction are first estimated, followed by the Stribeck friction parameters including the breakaway friction and Stribeck velocity. With the combined effects of viscous, Coulomb, and Stribeck friction, a complete feed drive model is attained.

The estimated model is then validated and compared with the tracking performance of the actual CNC machine. With improvements to the measured data and estimation method, these parameters can be monitored over time to evaluate the relative health of the feed drive.

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