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Data validation: a case study for a feed-drive monitoring

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***Abstract*-The monitoring of machine-tools implicated in the metal cutting process is the subject of increasing developments because of requests on control, reliability, availability of machine-tools and on work-piece quality. The use of computers contributes to a better machine and process monitoring by enabling the implementation of complex algorithms for control, monitoring, … The improvement of monitoring of the main machine-tools devices, the feed-drives and the spindles that drive the cutting process, can be realised by estimating their fault sensitive physical parameters from their continuous-time model. We have chosen to use a continuous-time ARX model. We particularly focus on slow time varying phenomena. This estimation should run while there is no machining process to avoid false detection of faults on the machine due to the cutting process. High speed motions, that occur at least for each tool exchange, are exploited. Some functional constraints require the use of an off-line estimation method, we have chosen an ordinary least squares method. Estimating the physical parameters is insufficient to obtain an efficient monitoring. A measurement analysis and validation are necessary as the validation of the estimated physical parameters. An approach of the measurement and physical parameter estimation validation for a NC machine-tool feed-drive is proposed.**

***Index Terms*-Adjustable speed drives.**

I. INTRODUCTION

The improvement of the machine-tool and machining monitoring mainly deals with fault detection, isolation and diagnosis. Therefore, the monitoring functions provide the information required by the maintenance, the supervision and the control system of the process and contribute to make it more reliable and more available. These information must also be reliable to take the right decisions in time. As fault detection is based on measurements, the analysis and validation of these data are necessary.

The paper is divided into four sections. First, we present the interests in monitoring the machine-tools and so their main devices: the feed-drives and spindles. Then we present a technique which enable this monitoring by estimating the physical parameters and its application to the feed-drive. The improvement in trusting the estimated parameters require, for the monitoring, the analysis and the validation of the measurements as the validation of these parameters. In the last section, we present the experimental feed-drive and experimental results of the data analysis and the physical parameter validation.

II. INTEREST IN MONITORING THE MACHINE-TOOLS

The numerically controlled machine-tools are major resources of the mechanical industry. They are often organised into autonomous flexible production cells with a usual monitoring. Three main parts represent the NC machine-tool: the control (numerical controller and programmable logic controller PLC), the axis (feed-drives, spindles) and corresponding auxiliary systems (gates, valves, detectors, …).

A. Usual monitoring of a NC machine-tool

The usual monitoring of a NC machine-tool is limited particularly to the machine-tool auxiliary component. The monitoring provides few data to supervision and control. Data are quite simple and do not require huge numerical treatments. These data consist of the work stage of the work-piece, the duration of use of the cutting tools and some indications about the machine auxiliary component failures or malfunctions. This monitoring is insufficient to make the machine-tool more accurate, more available and more reliable and to produce good quality work-pieces.

B. Interests in the feed-drive monitoring

Feed-drives and spindles are the main components of the NC machine-tool. They are directly implicated into the metal removal process. The accuracy, reliability and availability of the machine-tools depend on these devices that drive the tools. Different functions or activities like scheduling, maintenance, adaptive controls, diagnosis... require reliable information about the machine state and about its main components. This provide a better help for taking decisions and corresponding actions: stopping operation or changing operation, setting up, maintaining… For example, a reliable information reduce the risk of stopping operation due to a false fault detection.

C. Field and constraints of the feed-drive monitoring

The feed-drive monitoring field we consider is shown in Fig.1. It concerns the DC motor and the drive chain components. Generally, the DC motor faults and the drive chain faults are due to wear, heating, ageing. Their consequences are slow time varying phenomena (several months for the wear of guide ways…).

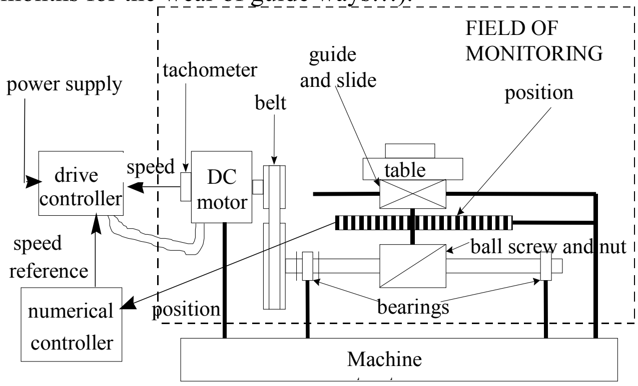

Fig.1 - Field of monitoring

If the monitoring of the feed-drive is running during the machining process, changes into some parameter values could be due to changes in the cutting process. So, the monitoring of the feed-drive is only considered while there is no machining process. To keep the machine-tool productivity, this monitoring will be done only during high speed motions generated by the numerical controller that occur at least for tool exchanges. For the need of the monitoring, we cannot use any high speed motion profile like speed reference added with a pseudorandom binary sequence "PRBS" because of two principal reasons: it accelerates the feed-drive ageing due to vibration and feed-drive motions may be too short to run the complete "PRBS". As a high speed motion has usually a trapezoidal speed profile which is typical of most machine-tool and because of the programming ability of the numerical controller, only the slope of this high speed motion profile can be adapted for the feed-drive monitoring..

III . PHYSICAL PARAMETERS ESTIMATION OF A FEED-DRIVE

A. Parameters to observe for the monitoring

The first step of the monitoring is the fault detection. Several fault detection methods based on process models exist [1]. Among them, we have chosen to estimate the physical parameters of the feed-drive continuous-time model. Indeed, some electrical motor faults are associated to their electrical physical parameters. Some experimental results [2] on a numerically controlled lathe feed-drive for different lubrication conditions and for different user's zone of the feed-drive allow to associate some faults to mechanical physical parameters. Table 1 shows the physical parameters of the feed-drive most representative of faults.

Table I. Faults and the sensitive physical parameters

Faults	**Sensitive parameters**
bearings and/or slide-ways wear	total dry friction torque C_d total viscous friction coefficient f_t
lack of lubricating oil and/ or lubricating oil ageing	total dry friction torque C_d total viscous friction coefficient f_t
no work-piece and/or work-piece holder	moment of inertia J_t
brush wear	Resistance R
motor heating	Resistance R, inductance L, torque coefficient K
demagnetisation	Inductance L, torque coefficient K

B. feed-drive continuous-time model

Estimating the physical parameters of a system requires a physical behavioural model of this system in which these parameters appear. The physical laws which describe the behaviour of the feed-drive concerned by the field of monitoring are:

for the electrical part:

$$u(t) - K.\omega(t) = L.\frac{di(t)}{dt} + R.i(t)$$

(1)

for the mechanical part:

$$K.i(t) - T_l(t) = J_t.\frac{d\omega(t)}{dt} + f_t.\omega(t) + C_d.sign(\omega(t))$$

(2)

where:

u(t): the tension applied to the DC motor
i(t): the induced current in the DC motor
ω(t): the revolution speed of the DC motor

and

L, R, K, J_t, f_t, C_d: are the physical parameters to observe for the monitoring defined on table I.

C. Feed-drive control

The most of feed-drives are activated by a permanent magnet DC motor and controlled according to the principle described by the following scheme:

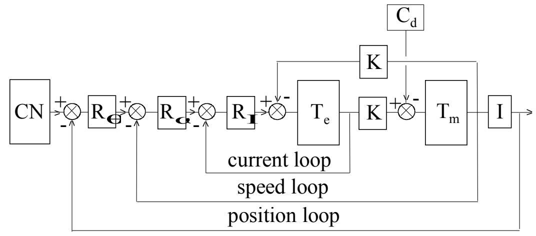

Fig.2 - Feed-drive control

R_θ, R_ω anf R_I are the position, speed and current controllers.

Te and Tm are the transfer functions of the electrical and the mechanical part of the feed-drive.

Different reference speed motions may be calculated by several numerical controllers (NC) from the work-piece program. We consider a trapezoidal reference speed. During the high speed motion, the supplied tension, the current and the speed of the DC motor have forms presented in Fig.3. Taking into account the constraints previously described, the physical parameters will be estimated from these variable forms.

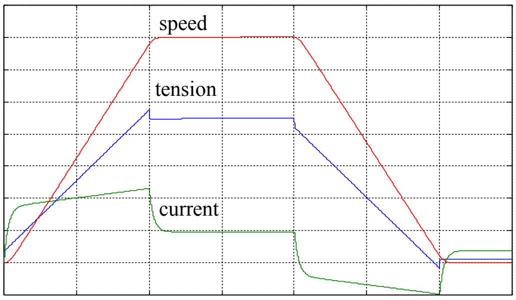

Fig.3 - Electrical and mechanical profiles of variables during a feed-drive high speed motion.

D. Physical parameters estimation

Several methods enable the estimation of the physical parameters from the estimated structural ones from a continuous-time model [3,4]. A linear regression parametric model has to be chosen in order to estimate physical parameters of a feed-drive. We have selected a continuous-time ARX model based on the derivative approximation of the current and the speed DC motor.

We have chosen the zero forcing#1 operator among the derivative approximation operator [3]. If "*x*" is a continuous variable, its derivative approximation operator is:

$$Dx(t) = \frac{0.2047x(t+h) + 0.886x(t) - 1.386x(t -}{h}$$

(3)

h is the sampling period for the discrete-time of measured variable "*x*" [3].

The derivative approximation of the current and speed of relationships (1) and (2) allows to write the corresponding linear regression parametric models:

$$u(t) = LDi(t) + Ri(t) + K\omega(t)$$

(4)

$$i(t) = \frac{J_t}{K} D\omega(t) + \frac{f_t}{K}\omega(t) + \frac{C_d}{K}$$

(5)

Each relationship can also be written:

$$[y] = [\Phi] \times [\Theta]$$

(6)

where θ is the parameter vector, y is the output vector and Φ the matrix of the measured data.

Because of the phenomena that affect the machine are slow time varying, recursive technique of estimation of the parameters is not necessary in this case.

Few non-recursive methods can be used to estimate the parameters of the chosen model. In this paper, we will only be interested in the ordinary least squares calculus, because one estimation of the parameter set per high speed motion is quite enough.

The parameters estimated by the ordinary least squares are:

$$[\hat{\Theta}] = \left[[\Phi]^T \times [\Phi]\right]^{-1} \times \left[[\Phi]^T \times [y]\right]$$

(7)

IV . DATA ANALYSIS AND VALIDATION

The validation activity generates credible, reliable and representative information of the measured physical variables [5,6,7,8]. The validation of the physical parameters estimated depends on the trust according to the measurements, the continuous-time model estimation and the estimation method. The chosen architecture of the parameter validation is described in Fig.3.

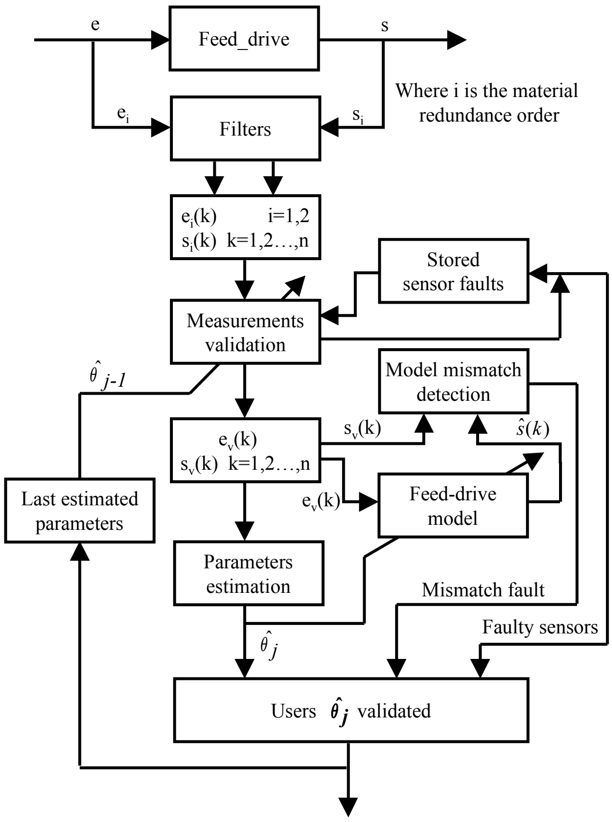

Fig.4 - Principle of the parameter validation

The measurement validation is based on material and analytical redundancies of needed measurements for the physical parameter estimation. Both measurement validation and model mismatch detection use statistical treatments. The validated measurements and the information about sensor fault and mismatch fault give credit to the estimated parameters.

Many kinds of error can affect the measurements: offset errors, gain errors and noises,...

A. Measurements filtering

A low pass filtering is adopted in order to reduce noise of the measurements. All the measurements are filtered the same way, that does not affect the identification if the filters are correctly chosen. This is shown in the following relationships:

$$H(s)=\frac{Y(s)}{U(s)}=\frac{Y(s).F(s)}{U(s).F(s)}=\frac{Y_f(s)}{U_f(s)} \qquad (8)$$

where H is the transfer function of the system to identify, Y is the output of the system, U is the input of the system, F is the transfer function of the filter, Y_f and, U_f are the filtered output and input.

B. Measurements validation

1) redundant measurements. For the other errors and in order to give more trust in the measurements, we propose the use of redundant measurements. An example is done in Fig.5 for current validation. These redundancies allow to detect and localise the faulty sensors.

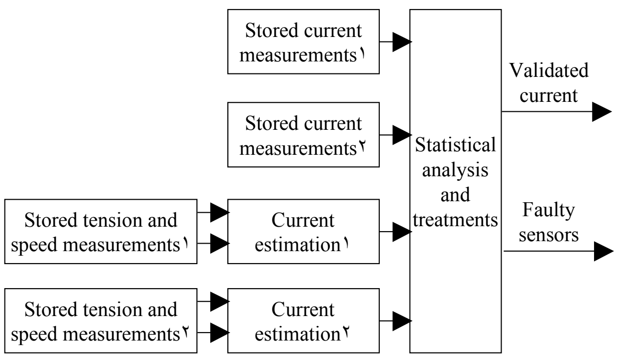

Fig.5 - Validation scheme for current measurements

The tension can be measured at the DC motor terminals but also by acquiring the tension reference delivered by the regulator to the electrical converter.
The revolution speed can be measured by tachometer and also by an incremental speed sensor used for the relative position determination.
There is no real existing redundancy for the measurement of the current. But as the current sensors have low costs and are easy to implement a second sensor can be used in order to obtain a material redundancy.

If the redundant measurements are too different it means that, at least one of the two sensors is faulty. Then, as the parameters are slow time varying, an analytical redundancy by estimating the current from (1) can be done with parameters that have been estimated and validated after the previous high speed motion.
As the estimation is done only once per high speed motion and as a potential decision to stop machining has to be taken before the tool is engaging into the work-piece, that generally leaves about one or two seconds to run all the treatments after the drop to the machining feed speed, they can be ended in time. We remark that the validation treatments may be run during the acquisition stage.
The identification technique we have shown requires quite a long time of high speed motion whereas the time of an high speed motion depends on the position where the machining stopped before the tool exchange. If the identification have not been run for a too long time, long enough high speed motions can be ordered to run a new identification.

2) Analysis and treatments.

Both current sensors used for redundant measurements can be modelled as follow:

$$I_{m\,i}=a_i.I_r+b_i+n_i$$

(9)

with: $i=1$ to 2, I_{mi} the measured current, a_i the measurement gain (should be 1), b_i the measurement offset (should be 0), n_i the white measurement noisy and I_r the real current.

The analysis of the residue between the two measured currents on different sliding windows allows to detect if there are measurement offset errors and/or measurement gain errors. This residue is:

$$r=I_{m١}-I_{m٢}$$

(10)

If the average of r is constant and not equal to zero, during the all high speed cycle, it means that there is an offset error detection on the measurement. If the average of r is not constant and depend on the current level, during the all high speed cycle, it means that there is a measurement gain error detection and perhaps a measurement offset error detection. In this second case, we can evaluate the importance of the measurement gain difference by calculating the following relative gain error:

$$E_r=١-\frac{a_١}{a_٢}$$

(11)

with $$\frac{a_1}{a_2} = mean\left(\frac{I_{m1f} - \bar{I}_{m1f}}{I_{m2f} - \bar{I}_{m2f}}\right)$$

(12)

$\bar{I}_{m1f} = mean(I_{m1f})$ and $\bar{I}_{m2f} = mean(I_{m2f})$,

where: I_{m1f} and I_{m2f} are the filtered current of I_{m1} and I_{m2}.

To isolate current faulty sensors an analytic redundancy of the current is obtained by the estimator presented on Fig.6.

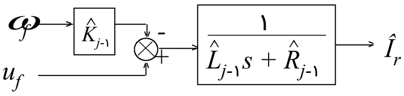

Fig.6 - Current estimation

$\hat{I}_r$ is supposed to be the real estimated current without offset error, gain error and noisy measurement because obtained from the validated and filtered speed ω_f and tension u_f and from last validated electrical parameter $\hat{K}_{j-1}$, $\hat{L}_{j-1}$ and $\hat{R}_{j-1}$ (see Fig.4). Indeed the existence of a numerical sensor in the redundant speed sensors makes easier the speed validation, the fact that the tension is the DC motor control input and there are two ways to measure this tension also make easier its validation. So, a ordinary least squares calculus allows to estimate the $\hat{a}_1$ and $\hat{a}_2$ measurement gain and the $\hat{b}_1$ and $\hat{b}_2$ measurement offset from these two relationships:

$$I_{m1f} = \hat{a}_1.\hat{I}_r + \hat{b}_1$$

(13)

$$I_{m2f} = \hat{a}_2.\hat{I}_r + \hat{b}_2$$

(14)

Using these estimated measurement gains and offsets, the detected sensor faults will be isolated and evaluated by comparing gain values to one and offset values to zero.

3) Validation of the estimating model

The detection of mismatch between the feed-drive and its model is justified the following way: if the system and the model do not match, this can be due to a sudden appearance of a fault in the system during the sampling horizon or of a fault due to the appearance of a phenomena not taken into account in the model like backlashes due to wear. So the parameters are not validated but their values can help for diagnosing the fault. Several methods can be applied like the residue whiteness test or a threshold logic technique …

V –EXPERIMENTAL RESULTS

The experimental platform shown in Fig.7 we have developed is composed of a DC motor (CEM T7F3B-1, 5.6 kW), a power converter, a numerical speed controller (DSPACE card for MATLAB™), and a drive chain components. This experimental feed-drive is equipped with redundant sensors (speed, current and tension), it allows to generate mechanical, electrical and sensor faults by the means of mechanical and electrical devices (brake, variable resistance…).

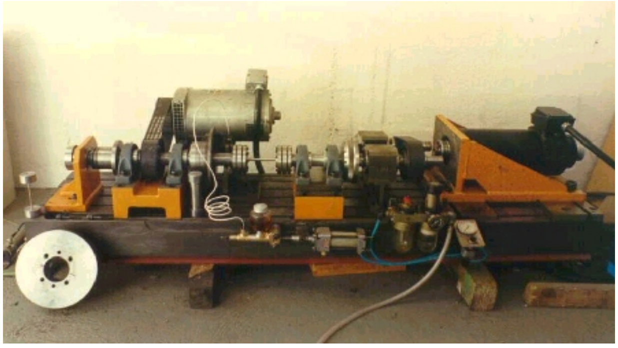

Fig.7 - Experimental feed-drive

The physical parameters of the feed-drive are estimated from the experimental data on Fig.8 using the method explained in section D.

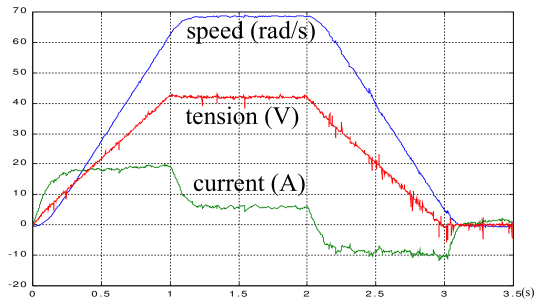

Fig.8 - Experimental data for the feed-drive physical parameters identification

To validate the measurement current, the analysis presented in section B is applied to the two experimental current I_{m1} and I_{m2} (see Fig.9). The residue between the two measured currents presented in Fig.10 is not constant and depends on the current level. It means the detection of a gain error at least.

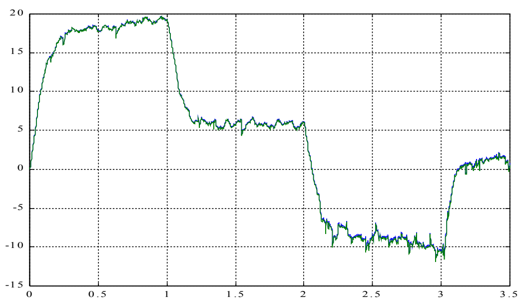

Fig.9 – Experimental measurement redundancy currents: I_{m1} and I_{m2}

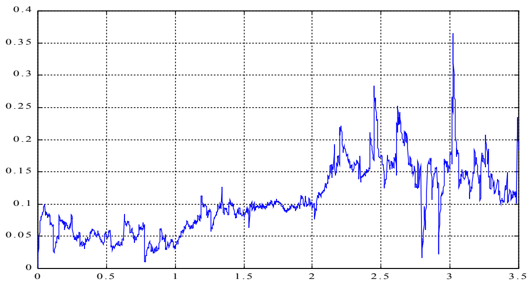

Fig.10 – Residue: r = I_{m1} - I_{m2}

To evaluate the gain error importance, the gain ratio drawled in Fig.11 is constant and calculated from (12) (it is equal to *0.9959*), so the relative gain error defined by (12) is equal to *0.41%*.

Fig.13 shows the measured and estimated current from which (13) and (14) give the estimated gains and the estimated offsets :

$\hat{a}_1 = 0.9962$, $\hat{a}_2 = 1.0007$, $\hat{b}_1 = 0.2212$ and $\hat{b}_2 = 0.0968$

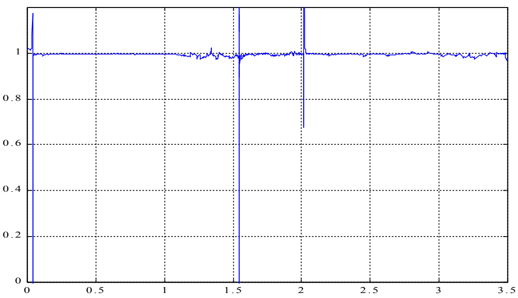

Fig.11 – Measured gain ratio: $\dfrac{a_1}{a_2} = 0.9959$

The results of the estimated gains and errors allow to accord more trust to the second sensor.

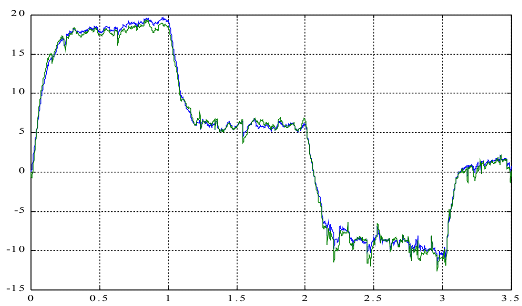

Fig.12 – Measured and estimated current: $\hat{I}$ and I_{m1}

Fig.13 presents the measured and estimated revolution DC motor with the validated current I_{m2}.

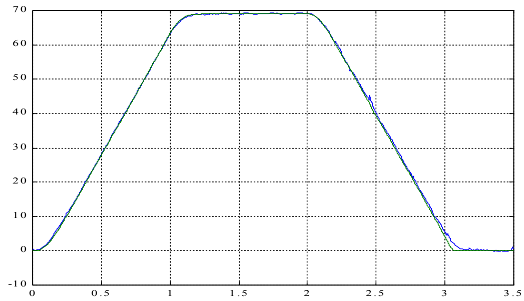

Fig.13 – Measured and estimated revolution DC motor speed

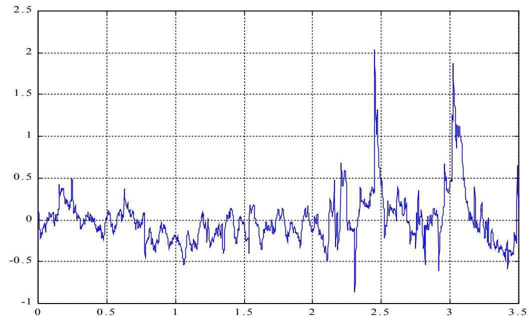

Fig.14 – Revolution speed residue between estimated and measured speed

To validate the mechanical estimating model, residue whiteness test or threshold logic technique analysis must be applied to the revolution speed residue in Fig.14.

CONCLUSION

Feed-drives and spindles are the main components of the numerically controlled machine-tool. They are directly implicated into the work-piece production. To improve the quality of work-piece, the reliability and availability of the machine-tools requires the monitoring of these devices as the cutting tool monitoring. Some feed-drive faults as bearing or slide-ways wear, lack of lubrication, oil ageing, brush wear, motor heating, … are associated to the physical behavioural model parameters. So, the first step of this monitoring is the estimation of the physical parameters. To avoid the cutting process influences, parameters estimation is done while there is no machining process, during the high speed motion of the feed-drive that occur at least for tool exchanges. Although the measured variables required for the used ordinary last square parameters estimation seems sufficient, we propose the validation of measured variables and continuous-time model to accord more trust to the physical parameters. It is based on material and analytic redundant sensors and on data processing and statistical analysis. Experimental feed-drive results presents a current faults sensor detection and isolation, and then a validation of the mechanical feed-drive model.

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