Development of Autonomous Machining Database at the Machine Level (Part 1) - Cutting Force Data Acquisition through Motor Current Sensing

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Abstract

Traditional process planning has relied on massive machining databases consisting of a selection of direct input-output mappings observed in remotely conducted experiments. The problem of unduly large sized database can be addressed by utilising well-proven analytical process models and populating the database with only the magnitudes of the model parameters that supposedly remain constant for a given work-tool material pair. However, even this approach cannot recognize the effects of variations in process state (e.g., such as caused by inclusions and the presence or otherwise of a built-up-edge).

This paper describes an alternative that utilizes a combination of axis motor current sensing using Hall-effect sensors, semi-inverse analytical modelling for database compilation, and forward modelling for prediction. The approach leads to the possibility of implementing distributed machining databases where each machine autonomously compiles its own machining database based on its routine shop floor experiences. The intent of this paper is to report on our findings with regard to current-force calibration and the effectiveness of current sensing as a substitute for the use of expensive dynamometers.

Keywords: Cutting force sensor, Motor torque, CNC turning

1. Introduction

The ability to anticipate the technological performances of the manufacturing processes involved is important in every phase—planning, monitoring, and control—of process engineering. With regard to machining processes, the performance measures of interest include cutting forces, cutting power, cutting temperatures, tool life, machining accuracy and part surface finish [1]. Often, these measures are interrelated. For instance, while programming a computer controlled numerical (CNC) machine to produce a part of specified geometry and accuracy, knowledge of the likely magnitudes of the quasi-static cutting force components along the machine axes is essential for ensuring that the torque/power capacities of the axis-drives are optimally utilized during roughing passes and that the cutter path is duly compensated during the finishing pass so as to achieve the desired part accuracy notwithstanding the geometric, thermal and force-induced deflection errors associated with the particular machining set up [2].

This paper addresses the problem of cutting force prediction with particular focus on turning operations performed on CNC turning centres. Firstly, certain problems associated with the traditional prediction method based on machining databases consisting of direct mappings between process inputs and outputs will be highlighted. Next, we will note how machining models have been used to reduce the database size but still suffer from an inability to take into account variations in the actual process state. This leads us to the description of a new prediction strategy being pursued by the authors. The new strategy utilizes a combination of axis motor current sensing, semi-inverse analytical modelling for database compilation, and forward modelling for cutting force prediction and leads to the possibility of implementing distributed machining databases where each machine could autonomously compile its own machining database based on its routine shop floor experiences. The main intent of this paper is to report on our findings with regard to current-force calibration and the effectiveness of current sensing as a substitute for dynamometer. Issues concerning semi-inverse modelling and forward modelling are still under investigation by the authors and will be presented in sequels.

2. Traditional Process Performance Prediction Strategy: Machining Databases Consisting of Direct Mappings Between Process Inputs and Outputs

Any prediction analysis involves two phases: a set of *informative* experiments, and the set of *future* experiment(s). The expectation is that the data we obtain from the informative tests will lead us to a reasoned statement concerning the performance of the future experiments. For this to succeed, there should exist a link—usually called the 'index set' in literature on statistical prediction analysis [3]—between the two sets of experiments. The stronger this link, greater is the confidence in our predictions.

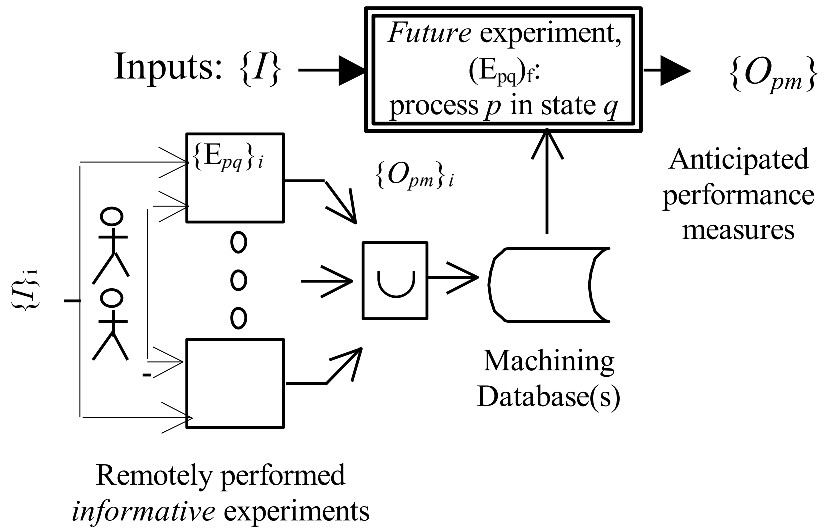

Fig. 1 Traditional approach to performance prediction in machining industry

Figure 1 shows the main features of the prevailing method of predicting process performance in machining industry. The 'index set' needed for predicting the performance of the specific local process of interest is derived from a machining database that captures direct mappings between process inputs, $\{I\}_i$, and the array of performance measure(s), $\{O_{pm}\}_i$, resulting from a large selection of 'informative' experiments conducted at several remote locations. Notwithstanding the popularity of this approach, several problems associated with it need to be recognized.

Figure 2 summarises the major factors influencing machining process performance. Here, the machining process, P_{pq}, could be the one involved in the informative or the future experiment. Subscript p denotes the type of process (contour turning, end milling, drilling, etc.) and subscript q denotes the state of the process (whether the process is associated with continuous chip formation with or without built-up-edge, discontinuous chip formation, chatter, etc.). Usually, the process-type, p, is known *a priori* but not its state, q, since the latter is often sensitive to input conditions represented by array $\{I\}$ which, in turn, can be composed as

$$\{I\} = \{I_{wt}\} \cup \{I_{tg}\} \cup \{I_{cc}\} \cup \{I_m\} \cup \{I_d\} \quad (1)$$

where the component arrays are as described in Figure 2.

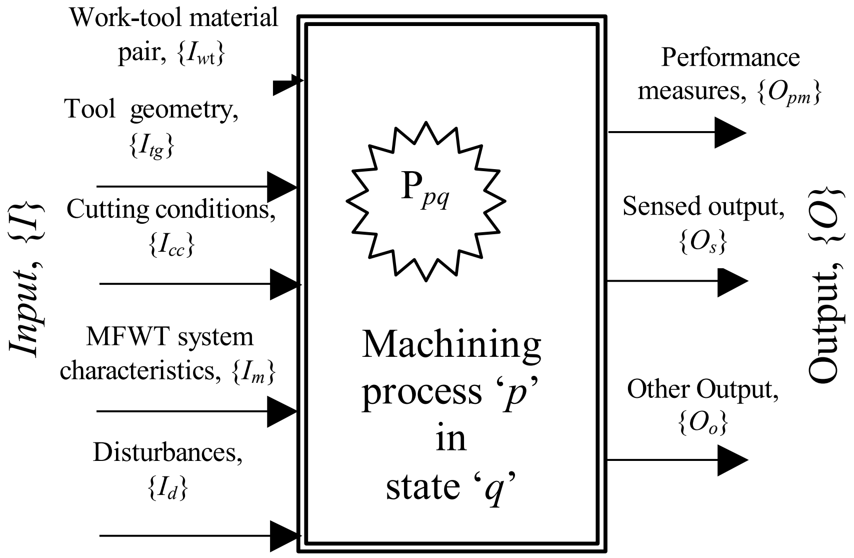

Fig. 2 Factors influencing the prediction of machining process performance

A vast number of CNC machines (even if we confine ourselves to turning centres) are in use across the world. Depending on the specific portfolio of parts encountered by the machine shop where it is located, each machine tool experiences a large variety of input vectors, $\{I\}_f$, that, in general, are significantly different from those experienced by other machines. The resulting combinatorial explosion means that, whatever the size of the machining database, it would be found to be too sparse to result in generally reliable prediction. The laboratories conducting the informative tests would have to keep working incessantly merely to catch up. Further, much of this 'informative' testing is quite expensive and time-consuming since it is performed in laboratory settings and requires significant human involvement and expertise. In addition, even if a database of substantial size is produced, only a tiny part of it is utilized in any given process planning exercise. Lastly, there might not be a close enough match between the process states in the informative and future experiments. A mismatch usually occurs because of differences in the (unknown) disturbance vectors, $\{I_d\}$, such as due to unexpected inclusions in the work material, variations in the heat-treatment states of work-stock, differences in initial conditions, and so on. Sometimes, the process could assume a different state, q, merely due to differences in the characteristics, $\{I\}_m$, of the machine-fixture-workpiece-tool (MFWT) structural systems. All this means that, quite frequently, predictions based on direct input-output mappings derived from tests conducted under remote laboratory settings turn out to be of dubious accuracy despite the high expense involved in compiling them.

3. Model-based Compilation of Machining Databases

In principle, the problem of unduly large-sized databases can be addressed by utilizing a suitable process model. Four types of process models have been explored in literature: empirical, mechanist, analytical, and computational. Of these, the last (utilising finite element or finite difference types of analysis) is not yet sufficiently mature to be of practical application.

An empirical model expresses the performance measure of interest as a power function of individual elements of the input array, $\{I\}$. (Taylor's tool life equation is a well-known example of empirical modelling.) The exponents of the elements are then stored in the database. This avoids the need for storing direct input-output mappings in the database, results in a much smaller database, and facilitates interpolation and extrapolation during the prediction phase.

Figure 3 summarises how database compilation based on mechanistic and analytical modelling is usually implemented. Mechanistic models assume that the cutting energy per unit metal removed depends mainly on $\{I_{wt}\}$, i.e., on the work-tool material pair. This helps reduce the size of the database. However, the influences of individual tool geometry parameters and the rest of the input factors are not recognized. As demonstrated by Armarego in a series of papers [1], this problem can be partially resolved by developing analytical models based on the assumption that the tool rake face is plane and that the shear zone is thin. Armarego starts with simple single edge orthogonal cutting experiments conducted in a laboratory setting and, for each work-tool material pair, measures the chip length as well as the power and thrust components of the cutting force (using a dynamometer) for a selection of tool normal rake angles and cutting conditions (cutting speed, and cut-thickness). He then applies his model of single edge orthogonal cutting with continuous chip formation without built-up-edge and stores in the database the resulting array of five supposedly 'invariant' model parameters. This phase may be called semi-inverse modelling since one works backwards from the output (cutting forces) to model parameters. (Full inverse modelling, i.e., estimating the inputs from the outputs is usually impossible because of the many-to-one relationship between the inputs and outputs.) Next, he develops an individual forward analytical model for each machining operation (turning, milling, drilling, etc.) to estimate the output cutting force components solely on the basis of the input tool geometry, cutting conditions and single edge orthogonal cutting database parameters.

The authors have had occasion to examine the effectiveness of Armarego's analyses against empirical single edge oblique cutting data gathered from diverse sources and have found that the analyses perform quite well with regard to qualitative trends in cutting forces. However, with regard to quantitative prediction, errors much larger than 10% are not uncommon. Apart from the errors arising from the simplifying approximations adopted in the analyses, the main reason for this quantitative inaccuracy appears to be the fact that the analyses have no mechanisms to take into account deviations of the actual process state from the state of continuous chip formation arising through a thin shear zone in the absence of a built-up-edge. Prompted by such observations, it was suggested in [4] that it should be useful to augment analytical modelling with process sensing where the sensor output is, somehow, strongly linked to the actual process state.

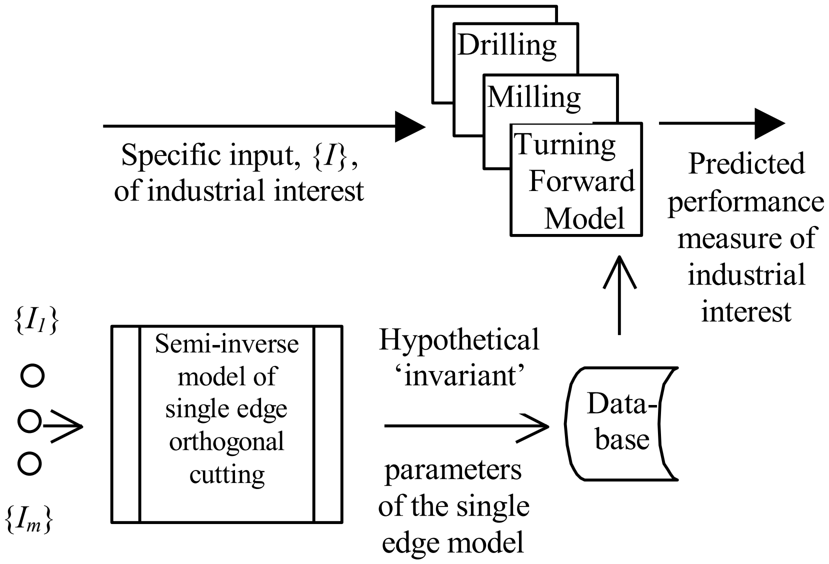

Fig. 3 Model-based compilation and utilisation of machining database

4. Autonomous Machining Databases

We have noted that the possible mismatch between the process states prevailing in the *remotely* conducted 'informative' experiments and the 'future' experiments impairs the accuracy and applicability of the index sets stored in the machining databases. In principle, this problem would not have arisen if both sets of experiments were conducted on the same work-tool material pairs and MFWT systems. This insight leads us to the vision of distributed machining databases where each machine autonomously compiles its own machining database based on its routine shop floor experiences.

With reference to Figure 4, suppose that each machine is equipped with a shop floor friendly cutting force measuring device. Initially, the machine's database would be empty. Hence, whenever the machine encounters a new work-tool material pair, one would have to revert to a conventional analytical model-based machining database (such as one based on Armarego's model) while designing the process plan. However, during the execution of the plan, the machine would have monitored the actual cutting forces. The database parameters could then be adjusted through an iterative application of the semi-inverse of the analytical model on which the initial index set was based. Thus, after a sufficient number and variety of learning episodes, the machine would arrive at an autonomously compiled a database that best suits its routine shop floor experiences. Whenever, the machine encounters a new machining job with a work-tool material pair that has a matching work-to material pair in the entries in its current state of database, it could simply retrieve the corresponding index set, insert in the forward model and predict (hopefully, much more effectively than possible with a conventional database) the cutting forces that are likely to arise. When a totally new material pair is encountered, the machine simply reverts to its database compilation mode.

5. Cutting Force Sensing: The Advantages and Limitations of Motor Current Sensing

For the autonomous database compilation strategy to succeed, each machine on the shop floor needs to be equipped with a cutting force sensing system. In principle, one could modify existing machine structures to incorporate some force-sensing elements or mount a separate cutting force dynamometer within the MFWT loop of the machine. However, except in sophisticated shop environments, either of these approaches is likely to be perceived as intrusive and unfriendly. We therefore need to look for a cutting force measurement system that is of acceptable accuracy and is easy to install and maintain on CNC machine tools commonly found in industry. Clearly, the system we are seeking a system that exhibits a one-to-one correspondence with the actual cutting forces and little else. This requirement rules out several process sensing strategies (such as acoustic emission sensing and the use of accelerometers) that have found successful applications in machining process condition monitoring. Amongst the strategies applicable for our present purpose is motor current sensing.

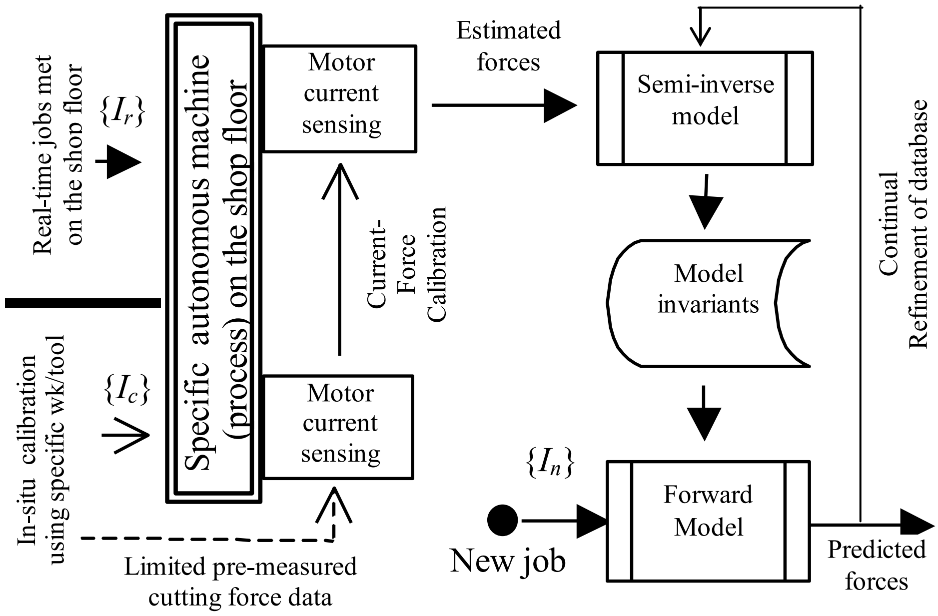

Figure 4 Use of autonomous databases compiled from real-time sensing (e.g., motor current)

Many commercial CNC machines are equipped with power meters mainly to help prevent machine overloading. Mannan and Broms are amongst the few who have studied the relationship between axis motor currents and cutting loads [5-7]. The method is particularly simple and inexpensive when a Hall effect sensor is used. All one needs to do is to pull out one or more of the power lines of the motor, slipin the Hall effect sensor(s) around them and reconnect the lines. Alternatively, if they can be accessed, one may use the motor current tapping points on the machine's drive system.

Broms [7] examined how the phase current of the three-phase a.c. induction motor driving one of the axes of a CNC machine changed when the axis was subjected to cutting load. He found that the range of the current (equal to twice the amplitude) increased with heavier cuts. To calibrate the effect, he applied known axis loads using a hydraulic cylinder. He found that the calibrations constants were variable. He then mounted thermocouples at strategic locations inside the drive transmission system and concluded that the variations in the calibration coefficients were mainly attributable to thermal effects within the drive system.

The focus of the work reported in [5-7] was on tool condition monitoring and adaptive control. The question of using motor current for compiling a cutting force database was not explored in sufficient detail. The rest of this paper will be mainly devoted to addressing this gap by calibrating the current signals against actual cutting loads, i.e., without the need for devices such as a hydraulic cylinder or a cutting force dynamometer.

Before proceeding to a detailed description of our work, one limitation of motor current sensing needs to be recognised. The total cutting force arising in any machining operation can be resolved into two orthogonal components where one of the components is normal to the machined surface. This force component may be said to be *passive* since, by definition, there is zero relative displacement between the tool and the workpiece in that direction. Experiments on machines equipped with a.c. motors have shown that motor current changes under drive load only when the axis is moving. No chnage in current is observed when the axis is stationary. This means that a.c. motor current sensing can only be used for measuring active forces and not passive forces. Thus, for instance, in a cylindrical turning operation, the method will not be able to measure the radial cutting force because it is passive. However, fortunately, this is not a serious limitation since CNC turning machines are generally utilised when complex contours are to be machined and, while machining a contour, invariably, there exist profile segments where all the three axes are in active motion.

6. Equipment Used in the Experiments

All experiments were performed on a 3-axis HITEC-TURN 20SII horizontal CNC turning centre (11 kW, 30-5000 rpm, 6-tool turret). Each axis (X: radial, Y: spindle, and Z: axial) was driven by a separate 3-phase AC induction motor. Speed control of each motor was achieved by frequency control. A change in phase frequency resulted in a corresponding change in the synchronous speed of the motor. The actual motor speed was slightly smaller than the synchronous speed (small slip).

The spindle motor had a base speed (N_b) equal to 1570 rpm (for machine code M41). Below the base speed, the phase voltage was proportional to the phase frequency so that the full torque of the motor was available. Above the base speed, the phase voltage was kept constant so that the motor operated under a constant power mode. X- and Z-motors always operated below their respective base speeds.

Hall effect sensors (RS 286-327) of sensitivity 0.1V/A were slipped around the input lines of the motors. Initially, each phase was monitored by a separate Hall sensor and the three current signals for each motor were combined into a root mean square value. Later, it was realised that it was sufficient to monitor only one phase of each motor if the goal was just to estimate quasi-static components of the cutting force. Reference values of quasi-static cutting force needed during the calibration and testing phases were obtained from a Kistler 9257B piezoelectric turning force dynamometer mounted on the tool turret.

Note that the dynamometer is used in our work only for demonstrating the effectiveness of motor current sensing. Clearly, during autonomous database compilation on the shop floor, there would not be a need for current sensing if a dynamometer were available on the machine. This issue will be clarified in Section 9.

7. Signal Processing

Both cutting force and motor current signals were collected using a data acquisition card at a sampling rate of 1000 Hz with the aid of LabVIEW software version 4.1. A preliminary set cylindrical turning and facing experiments was performed to test the ability of motor current to detect changes in cutting force. The tests yielded encouraging results with respect to active force components. Figures 5a and 5b respectively show a typical phase current signal drawn by the Z-axis motor and the corresponding cutting force signal, F_z, output by the dynamometer in a cylindrical turning operation. Denoting the mean current range during air cutting as I_{az} (A) and that during metal as I_{cz} (A), we note that $I_{cz} > I_{az}$. Following Broms [7], we expect that the rise in current range, $\Delta I_x = I_{cx} - I_{ax}$, would correlate with the cutting load.

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Figure 5 Typical original and de-noised Z-motor current signal and the corresponding dynamometer output signal in a cylindrical turning operation

In facing operations with radial in-feed, the amplitudes of the X- and Y- (spindle) motor currents exhibited significant changes at the moment the tool entered the workpiece. Further, as the facing operation progressed, the amplitude of the X-motor current remained fairly constant whereas the spindle motor current exhibited a linearly decreasing trend as the tool proceeded towards the work axis. However, in contrast, no sinusoidal variation in phase current (as in Figure 5) was detected when the Z-axis current was monitored. This was because this axis was aligned parallel to the passive force (F_p) arising in facing operations.

Several motor current signal de-noising techniques involving the use of frequency domain analyses and notch and low-pass filters implemented in electronic hardware were discussed in [7]. However, problems had remained with regard to the separation of regular frequency-dependent sinusoidal phase current variations from time-dependent variations due to changes in drive characteristics and cutting forces. In recent years, several techniques based on wavelet analysis have emerged where one can simultaneously examine both frequency-dependent and time-dependent aspects of a signal. A Debauchy-5 Level 6 or 10 wavelet based signal processing and de-noising technique involving 'diadic' sampling in the frequency domain has been found to be effective in the present study. The dynamometer signals corresponding to the three cutting force components (F_x, F_y, and F_z in directions X, Y, and Z respectively) were de-noised by subtracting the signal content in appropriately high frequency sub-bands. The moving average of the signal content in the lowest frequency sub-band yielded the quasi-static cutting force signal. Motor current signals were de-noised using a similar technique. Current signals in an appropriately low frequency band were found to exhibit the expected regular sinusoidal behaviour of phase current. The range I, (equal to twice the amplitude) of this signal component was taken as the preferred measure of the current signal. Both air-cutting and metal-cutting currents (I_a and I_c respectively) were recorded. Figures 5a and 5b also show the de-noised counterparts of the original signals.

8. Preliminary Observations and a Model

An analysis of the air-cutting signals from X-, Y-, and Z-motors (I_{ax}, I_{ay}, and I_{az} respectively) revealed that the speed of each drive was proportional to the phase frequency. The maximum frequency value for each feed motor (at 16Hz) was much smaller than that (184Hz) for the spindle motor.

A comparison of air-cutting and metal-cutting current signals revealed a pattern consistent with the following model. The mean value of the amplitude of current, I_j, drawn by drive motor j is indicative of the total quasi-static load, L_j, acting on it so that $L_j = \Psi_j(I_j)$ where Ψ_j is a continuous function. Now, note that the drive load, L_j, is usually made up of three basic elements—$W_{,j}$: the component of the weight of the moving parts in a direction *opposing* drive motion, $R_{,j}$: the frictional resistance of the drive motion, and F_j: the component of the externally applied cutting force in a direction *opposing* drive motion. Hence,

$$F_j = \Psi_j(I_j) - (W_{,j} + R_{,j}) \tag{2}$$

One can simplify the model by assuming that $\Psi j(I_j) = m_j I_j$ where m_j is constant for a given motor. Now, during air-cutting, $F_j = 0$ so that $m_j I_{aj} = (W_{,j} + R_{,j})$ so that

$$F_j = m_j(I_j - I_{aj}) = m_j \Delta I_j \tag{3}$$

where ΔI_j is the difference between the metal-cutting current (I_j) and the air-cutting current (I_{aj}).

Note that I_{aj} is the range (equal to twice the amplitude) of a current signal. Hence, it should always be taken to assume a positive magnitude. Likewise, R_j is always positive since it always opposes drive motion. In contrast, W_j can be positive or negative depending on the drive's orientation. If the drive is horizontal, $W_{,j}=0$. If the drive is vertical and the motion is downward, W_j should be taken to be negative in magnitude since it helps rather than opposes drive motion. Otherwise, W_j should be taken to be positive in magnitude. Thus, the term ($W_{,j}+R_{,j}$) can assume a positive or negative magnitude. However, we have noted that $m_j I_{aj} = (W_{,j}+R_{,j})$ and I_{aj} must have a positive magnitude. Hence, if $(W_{,j}+R_{,j})<0$, m_j would be negative, i.e., the metal-cutting current (I_j) would be smaller than the air-cutting current (I_{aj}). The opposite scenario would prevail if $(W_{,j}+R_{,j})>0$.

9. Calibration Using Statistical Regression

A major problem to be addressed concerns how one could transit from the world of motor current (expressed in Amperes) to the world of force magnitudes (expressed in Newtons). This problem was solved in [7] by applying a known force on the tool with the aid of a hydraulic plunger. Such an approach might be applicable in a laboratory but not necessarily on a shop floor.

The present authors suggest that one could use a set of standardised cutting tests as a substitute for the hydraulic plunger. This assumes that there exist work-tool combinations that generate fairly repeatable cutting forces under a given set of cutting conditions irrespective of the machine used. If so, the quasi-static cutting forces arising from one or more of these work-tool combinations can be measured with an accurate dynamometer at a *remote* site and the resulting force data supplied to the shop floor. The shop floor machine can then automatically replicate the recommended cutting tests and calibrate its own motor current signals against the remotely compiled but limited cutting force data. Based on this premise, motor current signals were calibrated in the present work against the corresponding cutting force data recorded by the piezoelectric dynamometer.

In order to establish the calibration curves, about 120 data sets were collected from experiments involving longitudinal turning and facing operations on one work material (cold rolled mild steel) with two different standard carbide tools (however, 95% of the calibration data were obtained with one of these tools) at various depths of cut (1 to 2.5 mm), feed rates (0.1 to 0.4 mm/rev), and spindle speeds (800 to 2400 rpm).

During the preliminary experiments described in Section 8, the air cutting current ranges observed for the feed motors (i.e., for X- and Z- motors) were found to be highly repeatable (i.e, they exhibited variances practically equal to zero) and essentially constant irrespective of the drive speed. This is understandable since these axes essentially work at very low speeds and, hence, one wouldn't expect significant nonlinear effects such as windage losses and temperature related fluctuations. Thus, for the feed motors, $\Psi_j(I_j)$ in equation 2 should essentially be a linear function. Based on these observations, I_{cx} data obtained from the cylindrical turning experiments were linearly regressed against the corresponding F_x data output by the dynaometer. A similar approach was applied to the I_{cz}-F_z data obtained from the facing experiments. The results are shown in Table 1. Note that the coefficients of determination (R^2) are around 0.94 for the X- as well the Z- axis.

The approach we need to apply for the Y-axis (spindle drive) is quite different. Firstly, in contrast to the Z- and X- axis, which are linear axes, our Y-axis is rotational. Hence, spindle motor current, I_y, cannot be directly related to the tangential cutting force, F_y. Rather one should perform the correlation with the cutting *torque*, T_y, which, in turn, can be expressed as $T_y = F_y r_e$ where $r_e \approx (r_w + a_p/2)$ where r_w is the work radius at the instantaneous location of the tool tip and a_p is the instantaneous depth of cut.

Secondly, unlike the X- and Z- drives, our Y-drive operates over a much larger and higher speed range (spindle speed, N= 800 to 2400 rpm). Across such a speed range, one would expect to see some non-linear effects such as windage losses and, as noted by Broms [7], some speed and load dependent temperature variations within the drive elements (e.g., owing to a change in the motor's electrical resistance due to a change in motor temperature). However, since temperature effects usually exhibit large time constants, one may assume that the drive parameters (e.g., m_y and R_y—see equation 2) would remain essentially unchanged at least during short bursts of metal cutting periods. This suggests that, for a high-speed axis such as the Y-axis on our machine, it is too simplistic to estimate cutting load directly on the basis of motor current range, I_{cy}. One would be better off by basing load estimation on the rise in current, ΔI_y.

Table 1: Calibration and Prediction Results

		Calibration based on curve fitting			Calibration and prediction by ANFIS	
		F_x	F_y	F_z	F_x	F_y
Calibration results	No. of calibration samples	13	102	105	103	240
Calibration results	Calibration equation using the following units: I_x, ΔI_y, I_z (A); F_x, F_y, F_z (N); T_y (Nm); r_w, a_p (m).	$F_x =$ - $198.45 I_x+258$	$F_y=T_y/(r_w+a_p/2)$ where $T_y=a(\Delta I_y)^b$ where the magnitudes of a and b are obtained from the polynomial (empirical) functions of N as given in Note 1.	$F_z =$ $215.9 I_z+0.003$	-	-
Calibration results	$R^{2\,\#}$	0.94	0.98	0.9427	-	-
Prediction results	No. of test samples	16	113	180	100	63
Prediction results	RMSE (N) *	29	36	27	34	21
Prediction results	R^2	0.837	0.9587	0.9427	0.96	0.94
Note 1: $a = a_{y3}N^3+a_{y2}N^2+a_{y1}N+a_{y0}$ and $b = b_{y3}N^3+b_{y2}N^2+b_{y1}N+b_{y0}$ if N> rpm, the base speed of the spindle motor, and $a_y = a_{y3}N^3+a_{y2}N^2+a_{y1}N+a_{y0}$ and $b_y = b_{y3}N^3+b_{y2}N^2+b_{y1}N+b_{y0}$ if N≤ rpm.						
Note 2: # Coefficient of determination, * Root mean square error						

The upper part of Table 1 shows the calibration results obtained for the three drives by applying the procedures described above. The following observations are worth highlighting:

(i) The calibration equations for X- and Z- drives are linear and independent of drive speed whereas that for spindle drive is non-linear (of power form) where the coefficient *a* and exponent *b* are in, turn, dependent on spindle speed, *N*.

(ii) The coefficient of I_x in the calibration equation for the X-axis (= -198.45 N/A) is negative whereas that of I_z (= +215.9 N/A) for the Z-axis is positive. This is explained by the fact that, unlike the Z-slide, the X-slide is vertically oriented and the drive configuration was such that, during radial in-feed, the weight, W_x, of the X-slide was aiding the motor drive in its drive effort. This is also the reason why the constant term (= 258 N) in the calibration equation for the X-slide is much larger (due to the weight-effect) than that in the equation for the Z-slide. These observations confirm the applicability of the simplified motor current model presented in Section 8. In order to be sure of our explanation, we performed some additional facing operations with radially outward motion. As expected, the air cutting current, I_{ax}, drawn during outward motion (= 19A) was much larger than that (= 13A) observed during inward motion—with half the difference attributable to the weight effect, Note also that, for each of the drives, the coefficient of determination is larger than 0.94.

(iii) The calibration curves for the Y-drive are non-linear (we had conducted a variety of non-linear regression analysis and, finally, noted that the 'power form' had yielded the best R^2-value), and a function of spindle speed, N—thus indicating the presence of speed dependent effects [7]. Note that the issue of the weight-effect does not arise with a rotational drive.

10. Force Prediction Effectiveness of Calibration Based on Statistical Regression

Nearly 300 additional data sets were obtained to test the prediction ability of the motor current calibration curves established in the previous section. The experiments included longitudinal turning, facing, taper turning, and contour turning (a limited number, but including profile angle variations of + ? to - ?°) operations performed on three different work materials (cold rolled mild steel, brass, and aluminium alloy 6061), three different carbide cutting tools, a range of depths of cut (1 to 2.5 mm), feed rates (0.1 to 0.4 mm/rev) and spindle speeds (800 to 2400 rpm). In each case, quasi-static values of air-cutting currents and metal-cutting currents for the X-, Y-, and Z motors as well as the corresponding quasi-static dynamometer readings were recorded. Next, the magnitudes of F_x, F_y, and F_z were estimated from the calibration equations (see Table 1).

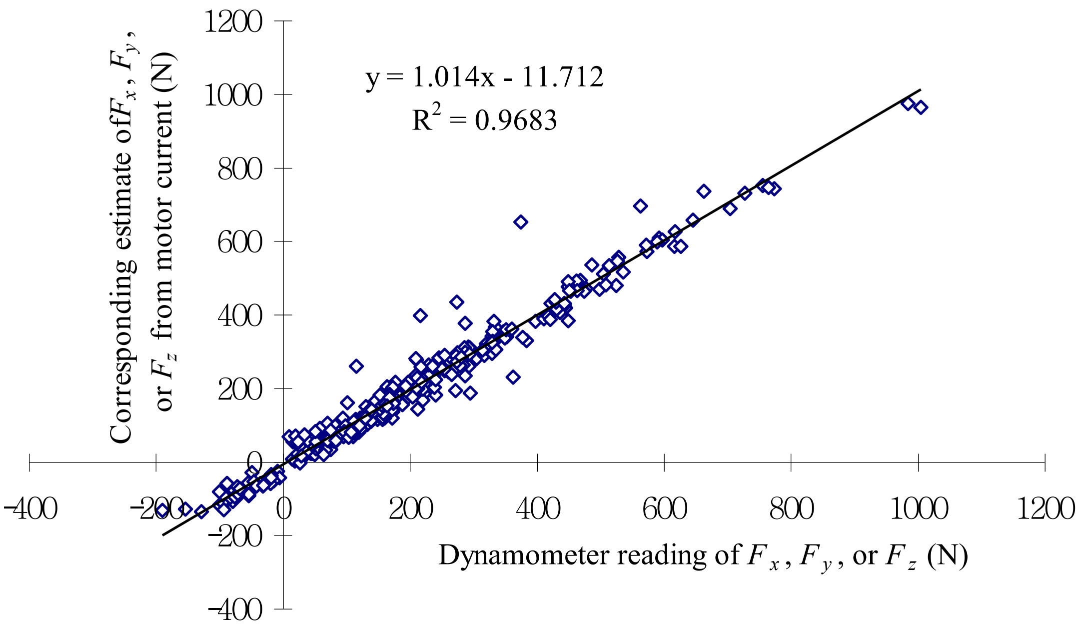

Figure 6 Effectiveness of force prediction on the basis of calibration equations established through statistical regression

Figure 6 shows the overall agreement between the motor current based estimates of F_x, F_y, and F_z and the corresponding actual force magnitudes as measured by the dynamometer. Note that, as one would desire, the regression line slope is nearly equal to 1, the intercept (=-6 N) is much smaller than the magnitudes of forces being measured, the coefficient determination (=0.97) is close to unity. Statistical analysis of the data in Figure 4 has shown that the maximum magnitude of condition-based 95% confidence interval is of the order of 35 N. The authors believe that this is acceptable from the viewpoint of machining process planning. We will attempt to clarify the source of this level of error in Section 12.

11. Calibration and Prediction using ANFIS

In the previous two sections, the force calibration and prediction exercises were performed through statistical regression. Statistical regression is just one of the techniques available for recognising input-output (I/O) patterns. Indeed, there are others. In recent years, several I/O pattern recognition systems based on artificial neural networks (ANN) have gained popularity. Amongst these, the Adaptive Neuro-Fuzzy Inference System (ANFIS) seems to be architecturally interesting. The authors had previously evaluated the effectiveness of ANFIS with regard to motor current based estimation of feed force [8].

ANFIS fuses fuzzy systems and neural networks into a single system and, thus, combines the benefits of the two. It has a fuzzy-system architecture, but uses neural learning technique so that it can be trained automatically. For a given set of input/output data arrays, ANFIS can construct a fuzzy inference system whose membership functions are tuned using a back-propagation algorithm in combination with the well-known least squares method.

As with any ANN approach, the use of ANFIS involves two phases. During the training phase, ANFIS identifies and stores (see [8] for details) the basic patterns implicit in a pair of input-output data arrays. The stored patterns are invoked during the testing phase to predict the outputs in response to new input arrays.

In view of the attractive features of ANFIS, we used it to re-evaluate the performance of motor current based cutting force estimation technique. The manner in which AFIS is implemented in this project is, in essence, similar to that described in [8]. A separate ANFIS was constructed for F_y, and F_z. Several input array strategies were explored: for T_y—{ ΔI_y, N, f}, {ΔI_y, N, a_p}, {ΔI_y, N, fa_p}, {ΔI_y, N, f, a_p}, and {ΔI_y, N}; and for F_z—{I_z, f}, {I_z, a_p}, and {I_z, f, a_p}.The actual dynamometer readings were used as the outputs during the training phase. The criterion for the selection of the best input array configuration was the minimum possible root mean square error yielded during the prediction phase. The right side of Table 1 shows the results. Note that, in comparison to the prediction results from calibration equations established through statistical recognition, ANFIS has been able to generally improve the prediction performance: the RMSE for F_y has decreased from 36 to 34N and that for F_z has decreased from 27 to 21N. While this improvement is welcome, it is not spectacular, thus indicating that we have arrived at the best possible calibration/prediction approach in the context of motor current sensing technique described in the previous sections.

12. Error Analysis

The statistical variances associated with the prediction results presented in Table 1 and Figure 6 cannot be totally attributed to the motor-current based force measurement technique. Some of it must be due to the inherent variability of the machining process. One way of clarifying this issue is to replicate the same cutting operation (i.e., the cutting operation is performed using the same work-tool material pair, tool geometry, and cutting conditions), noting the cutting force magnitudes output by the motor-current based system and the dynamometer, and performing a variance analysis. Here, we could assume that the Kistler dynamometer is highly accurate (at least in comparison to the motor-current based measuring system). Hence, the variance in the dynamometer readings can be assumed to be equal (approximately) to that of the machining process. This figure can then be subtracted from the observed variance in the corresponding motor-current based force estimate

Based on the above premise, several cylindrical turning tests were performed under nominally identical input conditions and the resulting variances of interest with respect to F_y and F_z (F_x could not be estimated through motor current measurement because it is the passive force in a cylindrical turning operation). The results (see Table 2) show that the variance attributable to motor current based technique is 260N^2 which is of the same order as the process variance (320N^2) estimated through dynamometer readings. The situation with the power component of cutting force does not seem to be that encouraging (variance of current based measurement is much larger than that of the process).

We next applied the F-test to the detailed data behind Table 2 to assess the significance of the difference between the mean force estimates yielded by the dynamometer and the motor current measurements. The tests indicated that, there was no difference between the mean F_z values at significance level equal to 0.05 whereas the difference was significant with respect to F_y.

Table 2 Variance Analysis

Row no.	Source	F_y		F_z	
		Mean (N)	Variance (N^2)	Mean (N)	Variance (N^2)
1	Dynamometer reading	485.78	84	325.78	320
2	Motor-current based estimate using ANFIS	465.21	425	326.87	580
3	Variance attributable to the motor-current based cutting force measurement technique = variance in row 2 – variance in row 1	-	383	-	260
Work material = aluminium alloy, tool holder = PDJNR2525M15, insert = DNMG150608-QM, insert angle = 55°, nose radius = 0.8 mm, side cutting edge angle = 93°, end cutting edge angle = 32°, ? clearance angle ?normal rake angle: -6°, and angle of inclination of major cutting edge =-7°. N=1000 rpm. a_p= 2mm. Feed rate = 0.2mm/rev. work diammeter was variable but was measured. No. of observations = 12.					

The superior performance of motor current based measurement of F_z may be attributed to the fact that this axis operates at low drive speeds and hence is unlikely to be subjected to speed and temperature dependent non-linearities and fluctuations. This is not the case with the measurement of F_y—hence the poorer performance. Clearly, further research is required if we were to improve the performance with regard to F_y. The authors are examining whether the performance could be improved by sensing temperature variations at strategic locations within the spindle drive (as in Broms' [7] investigations). However, it must be emphasised that the maximum root mean square error (RMSE) associated with motor current based force prediction is 34N (see Table 1). This figure does not compare unfavourably (in fact, more often than not, it is superior) with the RMSE values recorded by the authors when they had resorted to force prediction based on databases using direct input-out mappings (see Section 2) or databases relying on analytical modelling (see Section 3). In any case, it is quite likely that RMSE values of the order of 37N are acceptable in the majority of process planning exercises (with the possible exception of fine machining).

13. Conclusions

Conventional machining databases store direct input-output mappings for each process based on informative tests conducted at several remote locations under laboratory settings. The prediction accuracy obtainable from such databases is often dubious owing to the large and sparse nature of the databases. The problem of database size can be partially addressed by exploiting a suitable process model and storing in the database the model parameters that are supposed to be invariant for a given work-tool material pair. However, either of these approaches does not include a mechanism for recognising the actual state of the process which, as is generally known, could be influenced by unexpected variations in the inputs and the specific machine's structural characteristics. This paper suggests that, in principle, all these problems could be solved by enabling each machine to compile its own machining database on the basis of its routine shop floor experiences. The realisation of this vision requires each machine to be fitted with a set of shop floor friendly devices that are capable of measuring the performance measure being addressed. This paper has focused on the issue of cutting force measurement.

A motor current based technique for the estimation of quasi-static cutting force magnitudes has been developed and its practical effectiveness evaluated on a CNC turning centre whose three axes were driven by frequency controlled AC motors. Since the technique uses Hall effect current sensors and a simple software executing the signal processing and calibration procedures, the technique is easily automated and shop floor friendly. Further work is needed however to develop techniques suitable for machines equipped with other kinds motors. It is also useful to explore how the dynamic force components in end milling, etc. could be estimated using motor current signals.

The motor current based technique is applicable for measuring cutting force components along one or more of the axis motions. The method is not applicable when the desired force component is passive and is directed parallel to a machine axis. However, fortunately, this is not a serious limitation since CNC turning machines are generally utilised when complex contours are to be machined and, while machining a contour, there invariably are profile segments where all the three axes are in active motion. The current based technique may be supplemented by the part-inspection based technique described in [2] so as to be able to estimate every force component in every type of turning operation.

The performance of the motor current based technique is found to be superior while estimating the feed forces (F_x and F_z) to that while estimating the spindle torque. This phenomenon may be attributed to the diffrences in the drive speeds. The spindle invariably operates at a a much higher speed range and, hence, is more prone to speed and temperature dependent non-linearities and fluctuations. Further research is required to reolve this problem.

However, the maximum root mean square error recorded during the motor current based prediction exercises (using ANFIS) is 34N. It is believed that, except in the case of fine machining, this prediction accuracy comapares very favorably with that generally obtainable through conventional databases using direct input-out put mappings or index sets derived from analytical process models.

The results presented in this paper pave the way towards the autonomous compilation cutting force database by each CNC machine solely on the basis of its own shop floor experiences. The only caveat is that the machine needs to be provided with a standardised tool/work combination along with a limited cutting force data associated with it. However, identifying a reliable tool/work combination that produces essentially the same cutting force on every machine under nominally the same cutting conditions may not turn out to be a trivial task. Further work is required to resolve this issue.

14. References

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