SENSOR-BASED MODELING OF MACHINING OPERATIONS

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ABSTRACT
Some fundamental difficulties associated with developing industrially applicable models of machining are noted. It is suggested that progress towards the goal of industrial acceptance could be accelerated by integrating modeling with parallel developments in sensing and learning. Several such integration strategies are discussed.

1. INTRODUCTION

For over five decades, metal cutting scientists worldwide have been striving to develop reliable and robust models for machining operations. As a consequence, a variety of models are available today for predicting chip dimensions, cutting forces, temperatures, tool life, etc. Initially, these models were directed towards simple operations such as single edge orthogonal/oblique cutting which are rarely used in industry. However, these efforts were necessary to gain a deeper understanding of the machining process and to lay a foundation for modeling practical operations whose geometry tends to be much more complex. Indeed, in recent decades, these models have been extended to industrial operations such as turning, milling, and drilling.

The modeling efforts described above have provided us with a deep understanding of the varied manifestations of the machining process in different operations. To that extent, they have been valuable. However, generally speaking, modeling of machining continues to seriously lag behind the modeling of other metal deformation processes (e.g. rolling, drawing, extrusion, and forging) in terms of industrial acceptance.

The present paper examines some fundamental difficulties associated with the robust modeling of machining and suggests that progress towards the goal of industrial acceptance could be accelerated by integrating modeling with parallel developments in sensing and learning. The main intention of the paper is to stimulate discussion on the integration strategies.

2. DIFFICULTIES ASSOCIATED WITH MODELING OF MACHINING

2.1 Large Variety of Machining Operations

There exists a large variety of machining operations each requiring a tailor-made model. Turning is a continuous operation so that a steady state model suffices. In contrast, milling is an intermittent operation where the steady state is never reached owing to the continuous change in un-cut chip thickness. Unlike in turning and milling, the geometry of the cutting wedge is continuously varying along each cutting edge in drilling so that it becomes necessary integrate the effects along the edge.

2.2 Large Variety of Internal Variables

In predicting forces using the shear plane approach, one needs to know the mean shear stress on the shear plane which, in turn, depends on the combination of shear strain, strain rate and temperature at the shear plane. Hence, models for these internal variables are required. Further, there appears to be a natural order of variables in the sense that the preceding variable is needed in the prediction of the following one: chip dimensions $\rightarrow$ forces $\rightarrow$ temperatures $\rightarrow$ wear rate $\rightarrow$ tool life $\rightarrow$ economic performance measures [1]. Thus often, a series of models for specific sets of internal variables needs to be woven together in order to predict the desired output variable(s).

2.3 Difficulties in Determining the Work Material Properties

The magnitudes of strain, strain rate and temperature involved in machining are several orders higher than those that can be handled by current material test equipment. Further, the variety of work materials to be addressed by modeling of machining operations is several orders larger than that facing modeling of other metal processing operations. A way out of this problem is to recognize machining itself as a material test as advocated by [1, 2]. Armarego's school has been particularly successful in predicting cutting forces in a number of practical machining operations (turning [3], end milling [4], face milling [5], and a variety of drilling operations [6, 7] from a common data base of basic machining parameters influenced by work/tool material properties (shear angle, chip flow angle, edge forces, shear stress, and tool-chip friction coefficient amongst others) obtained from simple single edge oblique cutting tests on each work material.

Another problem that is crucial in finite element modeling is the selection of the chip separation criterion. Uncertainties continue to exist with regard to the use of limit strain and limit energy approaches.

2.4 Small Scale of Operation

The volume of material undergoing machining is much smaller than that in most other metal forming operations. Warnecke has amply demonstrated in his recent video [8] that the size, shape and dispersion of grains and metallurgical phases as influenced by heat treatment have significant influence on the nature of chip formation. An implication is that concepts of continuum plasticity may not be adequate and one may have to consider meso-plasticity. The small dimensions of cut also require us to recognize size-effect [9] and the influence of dislocations [10]. The cut dimensions are comparable to the magnitude of the cutting edge roundness (lack of edge sharpness) so that influence of stagnant zone and "ploughing" effects at the rounded cutting edge on cutting forces can be large [11]. No satisfactory models for these edge effects have so far been developed so that most cutting force models have had to make the unrealistic assumption that the cutting edge is perfectly sharp.

2.5 Non-unique Chip Geometry

The situation in machining is quite different from metal forming operations such as extrusion where the output geometry of the material being processed is fully determined by the tool (die) geometry. In machining, the chip can assume any thickness and there is much evidence that this often depends on the state of initial tool-work contact. In other words, the machining process is inherently not uniquely defined [12].

2.6 Large Variety of Modes of Chip Formation

Chip formation can take a variety of forms: type I: discontinuous chips, type II: continuous chips without built-up edge, type III: continuous chips with built-up edge, serrated chips, etc. Other aspects affecting chip form include the influence of chip formers and external obstacles encountered by the chip. The modeling approach required for each state tends to be quite distinct. Hence it becomes necessary to predict the mode of chip formation so that the appropriate model for predicting the desired output can be invoked.

2.7 Need for Large Machining Databases

As a result of the large variety of machining operations, work materials, internal variables, and states of chip formation to be addressed by machining operation modeling has required the support of large machining databases. We have already noted that the database used by Armarego for instance. However, the creation of these databases is an expensive activity requiring extensive off-line experimentation. This feature has been a major hurdle in transferring models to the industry.

3. THE MAJOR PROBLEM: MACHINING DATABASES (MDb)

It is clear from the previous section that industrially applicable machining models invariably require massive machining databases (MDb) consisting of data on the work material flow stress magnitudes, shear angles, chip flow angles, mechanical and thermal properties of the tool material, etc. An MDb is mainly required to guide the selection of the magnitudes of an array of model coefficients, {C}, used by the machining model, $[M_p]$, in predicting the desired array of performance measures, $\{O_p\}$, from the given array of nominal input variables, $\{I_n\}$ — see Fig. 1.

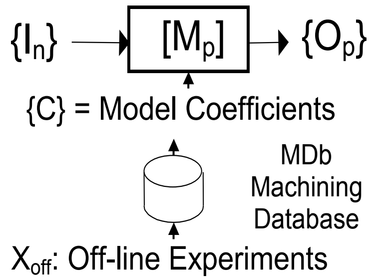


Fig. 1

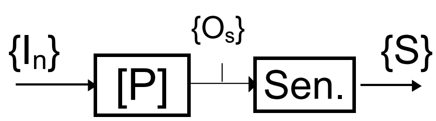
With regard to the MDb, two approaches are in vogue. The first attempts to obtain the properties of work materials from fundamental or, more appropriately, non-machining tests. The problem is that these tests need to be carried out at conditions approximating the large strains, strain rates, and temperatures prevailing in machining. Only limited success has been achieved in this regard so far. Further, the tests that are available are very expensive to conduct.

The second approach (pursued by Armarego, Venuvinod, etc.) utilizes machining (in particular, single edge orthogonal/oblique cutting) itself as the material test [13]. Methods are then found to extrapolate these data to more complex cutting situations.

Whatever the approach used, the creation of machining databases (MDb) requires extensive off-line experimentation, X_{off}, and is therefore expensive. Further, the database needs to be constantly expanded as each new work/tool material combination and tool geometry is encountered.

4. INTEGRATING MODELING AND SENSING

Sensing involves the measurement and monitoring of the desired subset $\{O_s\}$ of the process output and processing the signals collected through a signal processing algorithm or system to yield an array of sensed features $\{S\}$ — see Fig. 2.



Sensing

Fig. 2

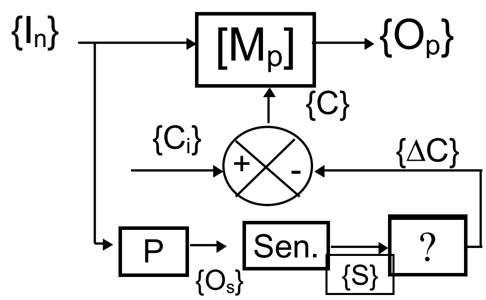
The following was noted in [14]:"[T]here is significant interest in sensing and monitoring. A more detailed study of the [literature] database has shown that much of this interest has appeared since the mid-eighties and that the sensing techniques have generally been augmented by Artificial Neural Nets and such AI-based techniques. On occasion, there has been a model-based processing of sensory data." Further, "[A]coustic emission has emerged as the predominant sensing technique in on-line process monitoring."

It was noted in section 3 that a major problem with traditional modeling approaches is the need to calibrate the model coefficients through a machining database MDb. Hitherto, machining databases have been compiled through extensive off-line experimentation. As we have noted, a reliance on such static databases leads to the inability of the model to perform effectively when there are minor perturbations in input conditions. These perturbations (inherent variability) cannot generally be anticipated and, owing to the inherently non-unique nature of the chip formation process, leads to large prediction errors.

In contrast, modern sensing technologies enable us to perform on-line or real-time measurement of outputs. Sensing and sensor fusion technologies are getting better every day. Is it time now to abandon the concept static databases in favor of dynamic databases, i.e. in favor of data obtained through on-line sensing? Such real-time data are likely to be superior to static databases since they have been collected while the same perturbations exist in the input conditions.

However, there is one problem to address. A model [M_p], is usually created to predict {O_p}. But the sensors measure {O_s}, which may or may not have an intersection with {O_p} — see Fig. 3. How can we solve this problem?

The answer probably lies in the realization that both {O_p} and {O_s} are outputs from the very same process [P] as the latter manifests in real time. Hence, {O_s} should contain much information concerning the way [P] behaves for the nominal input {I_n}. All we need to do is find a way of utilizing this insight towards determining the corrections {ΔC} that need to be made to the initial model coefficient set {C_i} derived from a static machining database.



Calibrating A Predictive Model by Using Sensed Output

Fig. 3

The author has attempted a variation of the above approach with some success in compensating for workpiece dimensional errors in turning [15].

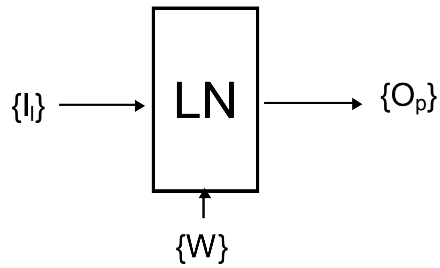
Finally sensing may also be helpful in identifying the operating mode of chip formation. For instance, AE-sensing might be able to identify, in real time, the mode of chip formation: e.g. Type I (discontinuous), serrated, Type II (continuous without built-up-edge), or Type III (continuous with built-up-edge, etc. Such identification is essential before one can invoke the appropriate predictive model if it exists (note that almost all the predictive models available today assume that chip formation is of Type II).

5. INTEGRATING MODELING, SENSING AND LEARNING

Learning is usually based on pattern recognition and clustering techniques such as Artificial Neural Nets (ANN). More recently, there have been applications of Chaos, Fractal, and Wavelet theories in signal processing to support more effective learning.

An ANN can be supervised or un-supervised. Amongst the various types of supervised ANN, the Back Propagation Net (BPN) has become particularly popular.

A supervised ANN operates in two modes: Training Mode, and Test or Utilization Mode. In the training mode a set of data/signals ({I_l} are input to the learning network. In addition, the network's connection weights [W] are adjusted to an initial set. Off-line experiments are conducted with the given process using a training set of {I_l} arrays — see Fig. 4. The sensed outputs {O_s} are used as training data to yield a set of corrections [ΔW] for [W]. The cycles are repeated until the network outputs signals, which agree with the experimental outputs within an acceptable error margin. [W]is then frozen so that the network becomes the trained network. The network can then be used to 'predict' the outputs for new instances of $\{I_l\}$.

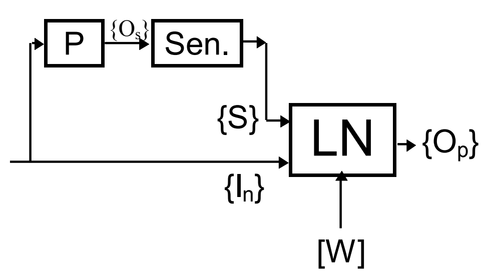


$\{I_l\}$: Inputs to the learning system
[W] : Matrix of Connection Weights
LN : Learning Network
Prediction by Using a
Learning System
Fig. 4

The performance of learning systems has been variable. Intuitively speaking, a learning system should be able to predict effectively if it is able to capture the essence of the process. It follows then that if the process were more complex (i.e. it has more uncertainty, more non-uniqueness, has a larger network of cause-effect-relationships, etc.) then one would require a more complex learning system.

What factors could influence the prediction effectiveness of a learning system? To the author's knowledge no rigorous answer is available today. Hence we will resort to the intuitive proposition that the learning effectiveness of a learning systems (such as BPN) can be increased by:
1. adopting a more complex network architecture (this is likely to increase the cost and processing time, hence we will leave it out of the present discussion);
2. increasing the number of training cycles (this also will increase the time required for training and, as encountered often in practice, there might be saturation effects; hence we will leave this alternative alone.); and
3. increasing the size of the input array $\{I_l\}$.

Let us focus on the last approach. How can we increase the size of the input array $\{I_l\}$? We have already used up all the known inputs. Hence we need to look elsewhere. How about $\{O_s\}$? The present modeling ethos assumes that it can down without a knowledge of $\{O_s\}$ in the prediction of $\{O_p\}$. This approach has only been partially successful. However, we have already noted that $\{O_s\}$ does contain some insight into [P] — see Fig. 5. If so, why not include $\{O_s\}$ as one of the inputs to the learning system?

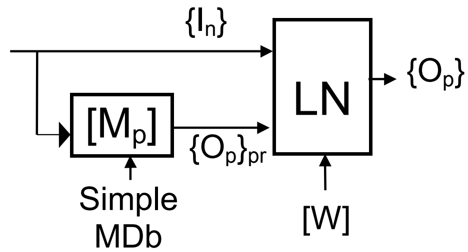


Augmenting a Learning System through $\{O_s\}$

Fig. 5

The above strategy might look similar to many recent works where a combination of sensing and learning has been used. However, in these works, the output to be sensed was both $\{O_s\}$ and $\{O_p\}$, i.e. one or more of the performance measures were also sensed. In contrast, in Fig. 5, there need be no overlap between $\{O_s\}$ and $\{O_p\}$. One may use only those sensors, which are convenient and are known to be able to reasonably capture the essence of the process and learn to predict any performance measure.

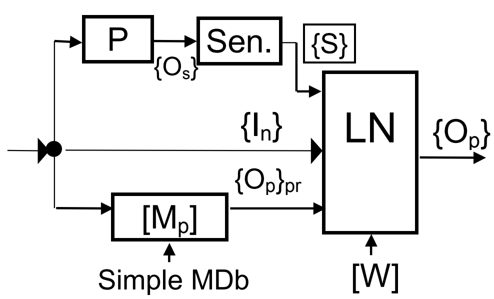
Another approach is to supplement the input array with model predictions — see Fig. 6.



Augmenting Learning with Modeling
Fig. 6

The predictions, $\{O_p\}_{pr}$, from the model contain much insight into the behavior of the process by virtue of the accumulated knowledge on machining that the model incorporates and the empirical information contained in its MDb. However, unlike in the case of conventional modeling, the model $[M_p]$ is not expected to perform accurate quantitative prediction. It is left to do what it does best, i.e. anticipate the qualitative trends of $\{O_p\}$. Augmented with this additional insight, hopefully, the learning system will perform faster and better. In contrast to the current practice, the MDb supporting the model need not be elaborate and highly accurate. The learning system will eventually learn to correct the errors arising from the MDb.

Fig. 7 shows another method of combining the benefits derivable from modeling, sensing and learning.



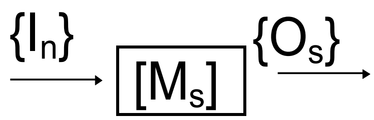
Augmenting Learning Through
Modeling as well as Sensing
Fig. 7

All the approaches described above have aimed at predicting $\{O_p\}$. With well-researched implementation, they are likely to be effective when (i) the sensing system measures the desired $\{O_p\}$, and/or (ii) the learning system is trained to learn $\{O_p\}$. However, what should one do when, as is often the case, one does not have sensors to measure $\{O_p\}$, or when no reliable off-line data exists to learn $\{O_p\}$?

To illustrate the above problem consider the case of sensing using acoustic emission (AE) signals which has become particularly popular in recent years. Many ANN based learning systems have been developed in association with AE. But, note that AE is not a performance measure. It is merely a conveniently sensed signal. How can the measured AE signals aid the process of predicting $\{O_p\}$? Clearly, much further research is required before one can find a satisfactory answer to this question.

Finally, consider the specific case of predicting cutting forces when AE constitutes the $\{O_s\}$. It has been observed that there is a strong correlation between 'True Mean Square (TMS)' of the AE signal and the measured cutting force components [16]. Thus it should be possible to gain much insight into the real-time process phenomena that influence cutting force magnitudes through real-time sensing of AE. Further, a learning system based on data obtained through $[M_p]$ may not need to have a very comprehensive MDb when the learning is augmented by AE. This is because the information obtained from the AE signals could be used to (somehow) calibrate the model or compensate for the errors in the model.

The above discussion suggests that it would be useful to direct a part of future analytical or computational modeling efforts towards developing an ability to predict $\{O_s\}$ (instead of merely predicting $\{O_p\}$) — see Fig. 8.



$[M_s]$ = The process model aimed at predicting $\{O_s\}$ — unlike $[M_p]$ which predicts $\{O_p\}$

Process Modeling for Predicting Sensed Output

Fig. 8

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