Expert System for Tool wear Monitoring in Blanking

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Abstract

This paper describes a simple yet powerful expert system created using the CRYSTAL shell which is able to monitor the potential and functional failures of the tool and the monitoring equipment. The techniques of feature extraction, selection and classification using the Bayesian rule are presented. Finally supervised learning, necessary when new situations are encountered, is also discussed.

Introduction

On-line tool wear and tool failure monitoring is desirable in an unattended manufacturing system since an unexpected interruption of the process for tool replacement due to excessive wear or fracture could halt production and even affect the quality of the product. The methodology used in this work namely, the acquisition of signals from sensors, the analysis of these signals in order to extract features which can give an indication of the condition of the tool and the classification of features by the use of Baysean probabilities are presented in this paper. The integration of this methodology with an expert system in order to provide an efficient, friendly, reliable and self-learning tool wear monitoring system is also presented.

Experimental design and results

The objective of characterising the blanking operation allowed numerous experiments to be designed in order to establish: first, the influence of tool wear on signals, the influence of other process variables having been reported previously [Mardapittas & Au, 89 & 90] and [Souquet, 90]; secondly, methods used to prevent the catastrophic failure of tools: and finally, a comprehensive knowledge base for the expert system.

Five signals in total were monitored, these are: (a) the displacement of the ram, used as a reference signal, (b) an optical device set above the stripper plate used only for monitoring slug returns and tool breakage, (c) the force encountered by the punch measured by incorporating a piezo-electric load cell in the punching tool, (d) the Acoustic Emission (AE) signal due to shearing and rupture of slugs was detected by an AE transducer with a frequency response of 100 to 950 KHz, this being fixed on the bottom plate of the pillar-and-die set and (e) a miniature accelerometer placed on the underside of the punch to measure the acceleration of the punch. All signals were sampled into a 386 PC using a 12-bit digital-to-analogue converter (DAC).

The variation of the force and rms AE signals with tool wear, for mild steel 1.2 mm thick, as well as the features extracted is shown in figure 1.

From figure 1, three features are found to be correlated to the wear on the blanking tools. These were: the AE energy at rupture, the force energy from tool impact to rupture and the displacement, Γ(B-A), from tool impact to rupture.

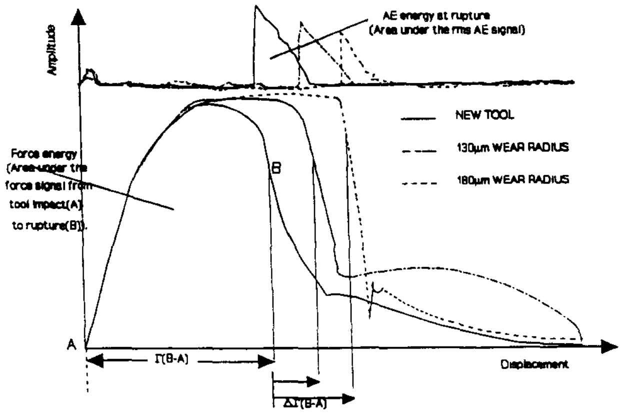
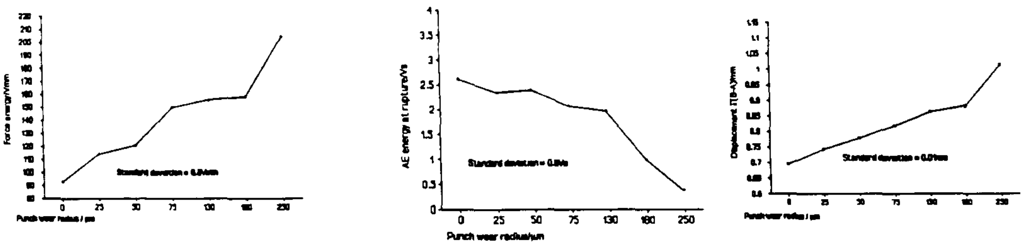


Figure 1. Typical blanking signals, showing variation with tool wear

Figure 2 shows the variation of these features with wear indicating their variability about their mean values.



(a) Force energy vs wear (b) AE energy vs wear (c) Γ(B-A) vs wear

Figure 2. Variation of useful features with progressive tool wear.

Since an expert system can only be as good as the knowledge that it possesses it is not surprising that the initial phase in the construction of the expert system namely, the gathering of knowledge, is the most important. One of the main features of the knowledge base is its ability to process and classify uncertain data. The problem of data classification and uncertainty is overcome by the use of Bayesian probabilities.

Data classification

Classifying data involves the assigning of a new object, that composes a set of features, to one of a number of possible groups. In blanking the tool life is partitioned into seven groups: group 1 corresponds to a new tool while group 7 to a tool with 250µm wear radius. Bayes' rule states that **an object should be assigned to the group with the highest conditional probability**. Hence if there are n groups an object will be assigned to group i if

$$P(G_i|x) > P(G_j|x) \qquad \textit{for} \quad i=1,2,\ldots,n \quad \textit{and} \quad j=1,2,\ldots,n$$

where P(Gi|x) is the conditional probability of the object being in group i given the set of features {x}. In practice however the probability P(Gi|x) is difficult to estimate, a more easily available quantity is the probability of getting a set of measurements {x} given that the object comes from a group i, P(x|Gi). Bayes' theorem relates P(Gi|x) to P(x|Gi) [James, 85]. Furthermore, the direct practical application of this inequality is difficult. In most practical applications a group is described by a set of variables or features where each variable is normally distributed and is typically described by two parameters: a mean μ and a standard deviation σ. Consequently a tool wear group would be described by a multivariate normal distribution with its centre given by a mean vector and its shape and spread by a covariance matrix. Thus applying Bayes' rule on the multivariate distribution we have

$$\frac{P(Gi)}{(2\pi)^{\frac{n}{2}}\,|\sum_i|^{\frac{1}{2}}}\exp[-\frac{1}{2}\,(x-\mu_i)'\sum_i{}^{-1}\,(x-\mu_i)] > \frac{P(Gj)}{(2\pi)^{\frac{n}{2}}\,|\sum_j|^{\frac{1}{2}}}\exp[-\frac{1}{2}\,(x-\mu_j)'\sum_j{}^{-1}\,(x-\mu_j)]$$

where μ is the mean vector, Σ^{-1} is the inverse covariance matrix and P(G) is the prior probability. Rearranging the above equation and considering a linear discriminant function, since the correlations between the variables are the same within each group, the following function is obtained,

$$-\mu_i\sum^{-1}x+\frac{1}{2}\mu_i^2\sum^{-1}-\ln(P(Gi)) < -\mu_j\sum^{-1}x+\frac{1}{2}\mu_j^2\sum^{-1}-\ln(P(Gj))$$

Letting $\mu_i\Sigma^{-1}$ = **Ci**, $-1/2\mu_i^2\Sigma^{-1}$ = **Coi** and considering the prior probabilities to be equal, the following equation is used to classify incoming data in order to identify tool wear,

$$Cix + Coi > Cjx + Coj \qquad \forall \qquad j \neq i$$

Expert system Implementation

The expert system, developed using the CRYSTAL shell, incorporates all signal processing techniques, data acquisition, feature extraction and classification, into its knowledge base in terms of rules. It takes control of the detection and identification of long time scale events such as tool wear and gives priority to the identification of short time scale events such as tool breakage, return of piece part with the punch (slug return) and malfunction of the sheet feeder mechanism so as to avoid catastrophic failures resulting from these short time scale events. Tool breakage and slug return are monitored using a simple optical fibre system. The expert system can also detect the working condition of the sensor and it provides a friendly interface with the user. Tests to determine the reliability and accuracy of this system provided a picture of its capabilities in the detection of any abnormalities during the blanking operation. A summary of the success rates and decision speed of the expert system is given below.

Sensor failure: detection rate is 100%, 20 tests for each sensor. The detection speed is 0.4s.
Malfunctioning of the feeder mechanism: 100% success rate, 15 tests for each material. The detection speed is 0.6s.
Slug return: for material thicknesses above 0.4mm the success rate is 100%, for thicknesses below 0.4mm the rate drops to 90%, 10 tests for each thickness. This was detected within 1.5s.
Tool breakage: no tests were performed due to the potential risk involved when forcing the tool to break.
Tool wear: The success rate is 85%, over 100 tests were performed for wear stages 1, 4 and 6; over 20 tests for other stages. Speed of wear identification is around 8s.

Conclusion

An expert system for tool condition monitoring in blanking has been successfully developed and implemented. The system can provide expertise in maintaining the product quality in real time. It is able to handle uncertain data, it is simple and user friendly and it can provide an accurate prediction on the condition of the tool. The system can improve itself with time as the reliability of the incoming data will improve when a larger number of samples is used and it can cope with new situations by adapting the knowledge acquired from a similar situation to the new one.

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