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A Novel Approach to Optimal Cutting Tool Replacement

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***Abstract*–**In metal cutting industries, mathematical/statistical models are typically used to predict tool replacement time. These off-line methods usually result in less than optimum replacement time thereby either wasting resources or causing quality problems. The few online real-time methods proposed use indirect measurement techniques and are prone to similar errors. Our idea is based on identifying the optimal replacement time using an electronic nose to detect the airborne compounds released when the tool wear reaches to a chemical substrate doped into tool material during the fabrication. The study investigates the feasibility of the idea, possible doping materials and methods along with data stream mining techniques for detection and monitoring different phases of tool wear.

***Keywords*—**Tool condition monitoring, cutting tool replacement, data stream mining, e-Nose.

I. Motivation

OPTIMUM performance of machining processes relies on the availability of the information about process conditions and feedback to the process controller. Among various process elements, cutting tool condition is one of the most crucial factors. It should be noted that considerable portion (7% - 20%) of machine downtime results from tool failure [1]. It has also been reported that successful implementation of Tool Condition Monitoring (TCM) can save up to 40% of production costs [2].

There are two major approaches for tool replacement. One based on empirical/statistical models of various process parameters such as tool material/geometry, work-piece material/geometry, feed rate, etc. These off-line methods usually result in less than optimum replacement time due to inherent nature of the models used. A more recent set of approaches are based on sensors measuring indirect process parameters such as force (dynamometer), acoustic emission, vibration (accelerometer), power, temperature, current, and work piece surface image. These sensors were either used individually or as multi-sensor suits along with various data processing techniques. A few research works have shown that these sensors can be efficiently used for the tool condition monitoring but with some limitations [3-8]. One of the limitations of these sensors is the use of indirect measurement that results in highly nonlinear mapping, including feature reduction and selection/transformation into hyper dimensional space to estimate the accurate tool wear conditions. These efforts usually result in considerable computational effort. As a result, majority of these efforts focused mostly on off-line applications.

From the review of relevant literature, it has been found that there is a significant need for a novel paradigm that can provide on-line and real-time tool condition monitoring without aforementioned limitations. The new paradigm for tool condition monitoring must be able to address the following questions:

- How fast can the suggested paradigm detect any changes in tool cutters during machining process? (fast on-line real-time response time issue)
- Can the suggested paradigm classify different stages of tool wear (e.g., fresh, slightly worn, severely worn) with high accuracy? (accuracy issue)
- How general the suggested paradigm would be to be used for various work-piece, tool cutter, and cutting parameter conditions? (generality issue)
- Can the suggested paradigm be a cost-effective and reliable option for metal cutting industry to accommodate? (economic feasibility issue)

In this study, a new paradigm for on-line and real-time tool condition monitoring that can address the aforementioned questions is introduced. This new paradigm employs the odor detection sensor, referred to as ***electronic nose or e-Nose***, for the first time as the core sensor for tool condition monitoring systems. In addition, cutting tools will be designed and fabricated in a new way that allows chemical compounds to be doped into their substrates. These new tool cutters are expected to significantly enhance the sensitivity of detecting precise tool conditions in real-time.

II. Research Focus

It is well known that machining processes such as turning and milling produce numerous gasses from the tribology of tool inserts and work pieces. The tool inserts and work-pieces are composed of multiple materials and as they engage each other at high temperatures, physical deformation and chemical reactions take place. Recently, advanced coating technology has significantly improved the tool life expectancy. Titanium Nitride (TiN), Titanium Carbo-Nitride (TiCN), Titanium

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Aluminum Nitride (TiAlN or AlTiN), Chromium Nitride (CrN), and Diamond coatings can increase overall tool life, decrease cycle time, and promoted better surface finish.

Our conjecture is that as machining progresses and tool starts to wear, the level of certain odorous compounds generated by the tool cutters will change overtime. It is based on the observation that the material used for coating tool cutters will gradually erode from the surface of the tool cutters as the tool wear progresses. For example, a TiCN coated tool will produce relatively large amount of Titanium based airborne particles as well as other gases at the beginning of its tool life when the tool is in fresh but produce less amounts of the same compounds as it gets worn down, and eventually produce no Ti compounds. This phenomenon can allow us to estimate the progress of tool wear by measuring the minute levels of specific airborne compounds produced from the tool cutters during the machining process.

Specifically, the following questions are posed:

- What type of chemical compounds and e-Noses would work best for the proposed paradigm in terms of response time and detection accuracy? How much, at what depths, and where on the tool geometry the chemical compounds must be doped into the tool cutters? Also, what doping method would be used?
- As the released odors quickly dissolve into the machining chamber air, which locations inside the chamber would ensure the best performance of the electronic nose?
- What would be the optimal range of cutting parameters that can ensure the best accuracy in estimating the tool life?
- What are the limitations of the proposed paradigm? For example, would the proposed paradigm work for both with and without coolant?

III. Available Technology

A. The Electronic Nose

Since its proposition of the concept in early 1980s [9], an electronic nose system has been used in many applications, especially in fragrance and cosmetics production, food and beverages manufacturing, chemical engineering, environmental monitoring, and more recently, medical diagnostics, and explosive detection. In principle, such systems have to rely on gas sensors, which were first developed more than 30 years ago [10, 11]. The electronic nose has been defined as a machine that can detect and discriminate among complex odors using a sensor array. An odor stimulus generates a characteristic fingerprint (or smell-print) on the sensor array. Patterns or fingerprints from known odors are used to construct a database and train a pattern recognition system so that unknown odors can subsequently be classified and identified.

As analytical instruments, these systems must be designed for long-term usage with high repeatability and reproducibility. Through e-Nose, not only the gas phase itself can be characterized but often also liquid and solid samples, as they often release volatile or semi-volatile components into the gas phase. It is well established that often a product's quality or the dynamic state of a process manifests itself in a special kind of odor. This is probably the reason why the nose is the main chemical sensor system with which human beings are equipped with. Therefore, an enormously wide market opens up for electronic noses (e-Noses) as condition monitors, provided that price, spatial requirements and energy consumption are compatible with the application [12]. The strictest requirements come from consumer applications of electronic noses in household appliances, air quality monitoring, fire detection, medical products, or automobile applications, where low cost and long-term stability combined with excellent gas sensitivity, gas discrimination, and response speed are necessary.

For more than a decade now, small and simple gas sensors which provide single output signal have been commercially available. However, these single output sensors allow only one component to be quantified, without the ability to distinguish between different gases or gas compositions. Moreover, these sensors usually suffer from cross sensitivity; in addition to their sensitivity to a particular target gas, they also show certain sensitivity towards other gases. Hence, a single output sensor cannot be sufficient for gas analysis, even if only one target gas has to be detected in a complex mixture of volatiles. The combination of several gas sensors (each providing a different sensitivity spectrum) forming a so-called sensor array can continuously deliver a number of signals, usually referred to as a signal pattern, characterizing the type and quantity of gases to which the array is exposed. The following table summarizes application of electronic noses (e-Noses) for various areas from the review of the relevant literature.

TABLE I
Application of Electronic Noses

Application Area	Examples
Food Quality evaluation	Discrimination of wines, fish freshness and potato chip flavors, etc.
Environmental monitoring	Water quality, air quality, and soil quality determination
Perfume and fragrance industry	Identification of perfumes
Automobile and Space Industry	Monitoring of air quality
Detection of Explosives	Detection of landmines
Medical Diagnosis	Bacteria identification and health quality assessment and quality control of pharmaceuticals
Mobile Robot Olfaction	Plume tracking, Odor Source Localization, Trail Following

B. Data Analysis Using Data Mining Techniques

The appropriate and innovative data mining techniques are presently being used to determine the presence of certain doping material based on e-nose data. A common by product of many industrial processes, SO_2, is used as our initial target chemical. The e-nose stream mining to detect traces and different concentrations of SO_2 in the machining chamber air involves three main steps: dimension reduction, classifier training, and real time data transformation and classification.

1) Dimension Reduction

The chemical data collected by the e-nose will include many different gas components. Data in such high dimension space must be "compressed" into a smaller dimension space so that classification methods can be applied effectively. For this purpose, we are using Principle Component Analysis (PCA), a computationally inexpensive technique which has been used in a number of applications including analysis of gas sensor data. In theory, PCA is considered an optimal linear scheme for compressing high dimensional vectors into lower dimensional vectors. For non-linear data, a Kernel PCA is used.

2) Classifier Training

At this stage, a binary Support Vector Machine (SVM) classifier is created using sample data collected in previous phase as training. Our sample data are obtained during two types of machining operations, those with doping material (Sulfide or Nitrate) and those without. The samples collected with doped tool will be significantly different from those obtained without it. SVM is a relatively new method that has been shown to be effective in classifying both linear and non-linear data without suffering from the over-fitting problem exhibited by some neural network and decision tree approaches. For linearly separable data, SVM classifier defines an optimal separating hyper-plane which is equal distance to data points on the borderline (called supported machine) of the two data sets. For non-linear data, as is the case in non-linear PCA, the original data must be converted into linearly separable higher dimensions by using the appropriate kernel function. Thus, the performance of the SVM is greatly influence by the kernel function selected [13]. In phase I of our study, we will test various common kernel functions, shown in Table II to identify the most suitable one. It should be pointed out that although SVM is known to be computationally expensive, its training is done before the system is brought online and thus does not affect the real-time performance.

TABLE II
EXAMPLE KERNELS

Polynomial	$K(x,y) = \left(\langle x,y\rangle + 1\right)^p$
Gaussian Radial Basis Function	$K(x,y) = \exp\left(-\frac{\lVert x-y\rVert^2}{2\sigma^2}\right)$
Multilayer Perceptron	$K(x,y) = \tanh\left(\rho\langle x,y\rangle + \gamma\right)$, where ρ, γ are sca and offset.
Fourier Series	$K(x,y) = \frac{\sin\left(N+\frac{1}{2}\right)(x-y)}{\sin\left(\frac{1}{2}(x-y)\right)}$
Additive	$K(x,y) = \sum_i K_i(x,y)$

3) Real-time Data Transformation and Classification

The SVM classifier created in the previous step will be used to determine the presence of SO_2 (and other compounds considered) in real-time. Due to the difference in tools and cutting material, it is possible that the gas composition from this data could different from training data in terms of baseline values and scales. A suitable data transformation function such as normalization transformation is used to convert the real data to the same scale and baseline of the training data. The appropriate transformation function is identified by comparing the initial real-time data sample with doped training data. Once established, this function is used to efficiently convert all remaining data before they are analyzed by the SVM classifier. In addition, an appropriate window size is also determined through experimentation to achieve the right level of sensitivity. Specifically, window size should be small enough so that the classifier will focus on the most recent data and detect presence of SO_2 as early as possible. However, the window size should also be large enough to avoid being over-sensitive, false reporting of SO_2 presence due to data fluctuation and noise.

IV. Doping of Chemical Compounds in Tool Cutters using CVD

Chemical vapor deposition (CVD) process has been developed as a technique for creating thin films of a large variety of materials on other substances [14]. In a typical CVD process, reactant gases enter the reaction chamber. The gas mixture is heated as it approaches the heated deposition surface. Depending on the process and operating conditions, the reactant gases may undergo homogeneous chemical reactions in the vapor phase before striking the surface. Near the surface, chemical concentration boundary layers form as the gas stream heat and the chemical composition changes. Heterogeneous reactions of the source gases or reactive intermediate species occur at the deposition surface forming the deposited material.

The advantages of CVD process are: versatile – can deposit any element or compound; high purity – typically 99%; high density – ranging 94-97%; material formation well below the melting point; coatings deposited by CVD are conformal and near net shape; and economical in production, since many parts can be coated at the same time [15]. There are basically two different types of CVD process used in the industry: metal organic CVD and plasma enhanced CVD. In metal organic CVD a layer of one substance grows on a single crystal of another. Plasma enhanced chemical vapor deposition (PECVD) is performed in a reactor at temperatures up to 400 °C. There are several applications of the CVD process. The most important of them are microelectronics, manufactured diamonds and protective coatings.

V. Feasibility Analysis of e-Nose (Phase I)

In this research phase, commercially available e-Nose (ArtiNose) is used to test our main hypothesis. Note that in this phase, tool cutters are not doped with any chemical compounds. The main focus is the feasibility analysis of the e-Nose for tool condition monitoring system where a data mining technique, referred to as support vector machine (SVM), is employed as a main classifier of tool wear conditions as illustrated in Fig. 2. In this phase, normalized and tempered AISI 4340 medium carbon low alloy steel blocks with an average hardness of 26 HRc are used for the experiment. This alloy steel is widely used in the fabrication of machine tool structural parts, power transmission gears and shafts in the automotive industry, and aircraft landing gear parts. In addition, chemical vapor deposited (CVD) multi-layer TiAlN–TiN coated Kennametal KC725M grade carbide 10mm IC end-milling inserts are used for the study (ISO designation of SPET10T3PPERGB). The insert thickness is 3.96mm with an overall coating thickness in the range of 3–5μm. The substrate material consists of tungsten carbide with an 11.5% cobalt binder.

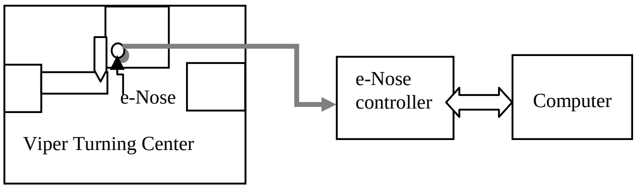

Fig. 1 Experimental setup for Phase-I

The tough CVD coating material and the thermal shock resistance of the substrate makes this insert suitable for both semi-dry and dry machining applications. In addition, a CNC turning center (Viper VT25B with Fanuc Oi Mate-TC controller) is used. The following table summarizes the experimental design for the Phase-I:

TABLE III
DESIGN OF EXPERIMENTAL PARAMETERS

Parameter	Level
Location of e-Nose	Turret, Spindle, Chamber
Cutting speed	Low, High
Feed rate	Low, High
Depth of cut	Low, High
Coolant	On (wet), Off (dry)
Tool class	Fresh, Medium, Severe

Note that tool classes are defined based on the maximum level of flank wear and are measured using a digital microscope (Video Direct Microscope, QVI Inc.). In this phase, we collected 8 × 3 × 3 × 2 × 3 (replications) = 432 data points from the experiment. Out of total 432 data points collected, we used 288 (2/3) data points for training of SVM classifier and remaining 144 (1/3) data points for testing purpose. Specifically, the training and test is based on the architecture given in Fig. 2.

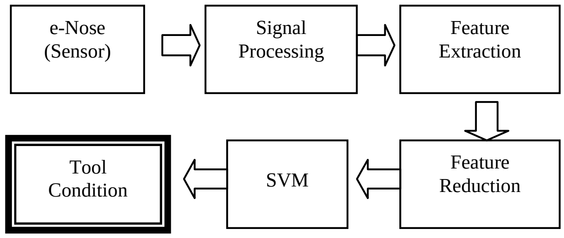

Fig. 2 Architecture of tool condition monitoring in Phase-I

The SVM and other reduction methods are implemented using WEKA ML suite, which provides a freeware environment supported by many machine learning authorities [16]. At present time, the data collected is being analyzed. It should be emphasized here that the results from the Phase-I will be used to address the main research questions outlined earlier. By employing the SVM in the architecture, which is known to be fast and accurate, e-Nose is expected to provide some level of success in on-line and real-time tool condition monitoring. However, we speculate that its performance in terms of speed and accuracy may not be promising because of the limitation of the architecture that uses single e-Nose, uses no chemical doping, and has a computational overhead.

VI. USE OF E-NOSE AND CHEMICAL COMPOUND DOPED TOOL CUTTERS (PHASE II)

In this next research phase, to significantly improve the performance (speed and accuracy) of tool condition monitoring, cutting inserts will be designed and fabricated to have chemical compounds doped in their substrates. Several chemical compounds that have a high diffusive rate and no effect on cutting insert properties will be considered as dopants. Examples of such chemical compounds include small amounts of certain Sulfides and Nitrites. Once potential compounds are determined, they will be diffused into the boundary of tool substrate (~10μm depth from the top) and coating material and another layer in the substrate with the depth of 400μm from the top of the tool insert as shown in Fig. 3. The CVD process will be used for the doping of chemical compounds at the boundary between coating and substrate material and rapid tooling technology will be used to have another inclusion of the chemical compounds at 400μm depth boundary. Different stages of tool wear such as medium wear and sever wear can be accurately estimated by having these chemical compounds at different depths in the tool inserts.

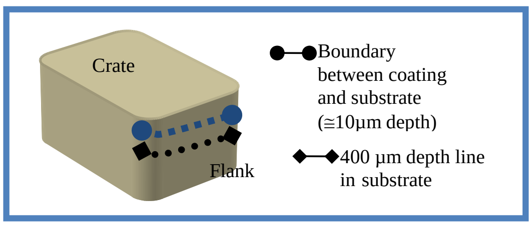

Fig. 3 Tool inserts with inclusion of chemical compounds for Phase-II

Once the tool inserts with chemical compounds are prepared, we will conduct experiments similar to the ones given in previous section. In this phase, the architecture of tool condition monitoring shown in Fig. 4 will be considered. In the final form of the architecture, the data mining technique such as feature extraction, selection and support vector machine learning are not required once the stream mining algorithm is trained to detect dopants signal print. The dynamic signal profile generated by the real time mining of the e-Nose data will help us identify different phases of tool wear. It is hypothesized that automating the data mining layer in the proposed architecture will satisfy the speed and accuracy requirement of tool condition monitoring for on-line and real-time applications of the concept. The experimental results from this phase will be compared to the results from the Phase-I to test the hypothesis. Note that the performance of the proposed architecture depends on the sensitivity and reaction time of the e-Nose used to the doped compounds.

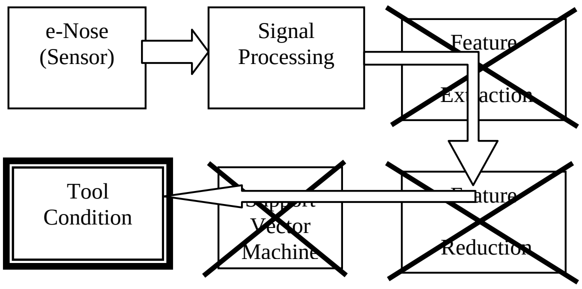

Fig. 4 Architecture of tool condition monitoring in Phase-II

VII. Conclusion and Future Research

This paper briefly outlines the original idea of using e-Nose and its associated data stream mining techniques for tool condition monitoring. At present time, the experimental setup dealing with feasibility studies of the proposed hypothesis is underway. The identification of the possible chemical compounds as the doping material on high speed steel cutting inserts is also being studied. Due to the proprietary nature of the proposed method and pending patent application, many of the technical details were not presented in the paper at this time. However, as the experiments are finalized and the e-Nose stream mining algorithms for the specific chemical compounds considered are refined through training; several follow up publications are planned.

In addition to the main trust of the research activities outlined, other aspects of the problem given below are also identified for future research.

- Slow response time of e-Nose to chemical compounds: We plan to experiment with different concentrations of dopants by manipulating the parameters of the doping process.
- Tool material properties may be changed due to doping of chemical compounds, for example, reduced hardness: During the dopant selection process, special attention will be paid to the compounds that will not affect the physical and functional properties of the cutting edge. The high temperature and oxidation properties of the chemicals will be investigated along with possible hazard to humans.
- The location of the e-nose in the cutting chamber will be studied by considering the highly dynamic air flow properties in the chamber due to fast moving parts. This will be an important factor in determining how quickly and in what patterns the airborne particles will be dissolved into cutting chamber air.

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