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Condition based maintenance-systems integration and intelligence using Bayesian classification and sensor fusion

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Abstract System integration in condition based maintenance (CBM) is one of the biggest challenges that need to be overcome for widespread deployment of the CBM methodology. CBM system architectures investigated in this work include an independent monitoring and control unit with no communication with machine control (Architecture 1) and a data acquisition and control unit integrated with the machine control (Architecture 2). Based on these architectures, three different CBM system applications are discussed and deployed. A verification of the third system was done by performing a destructive bearing test, causing a spindle to seize due to lubrication starvation. This test validated the CBM system developed, as well as provided insights into using sensor fusion for a better detection of bearing failure. The second part of the work discusses intelligence in a CBM system using a Bayesian probabilistic decision framework and data generated while running validation tests, it is demonstrated how the Naïve Bayes classifier can aid in the decision making of stopping the machine before catastrophic failure occurs. Discussing value in combining information supplied by more than one sensor (sensor fusion), it is demonstrated how a catastrophic failure can be prevented. The work is concluded with open issues on the topic with ongoing work and future opportunities.

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Keywords Condition based maintenance · Machine control integration · Naïve Bayes classifier · Sensor fusion

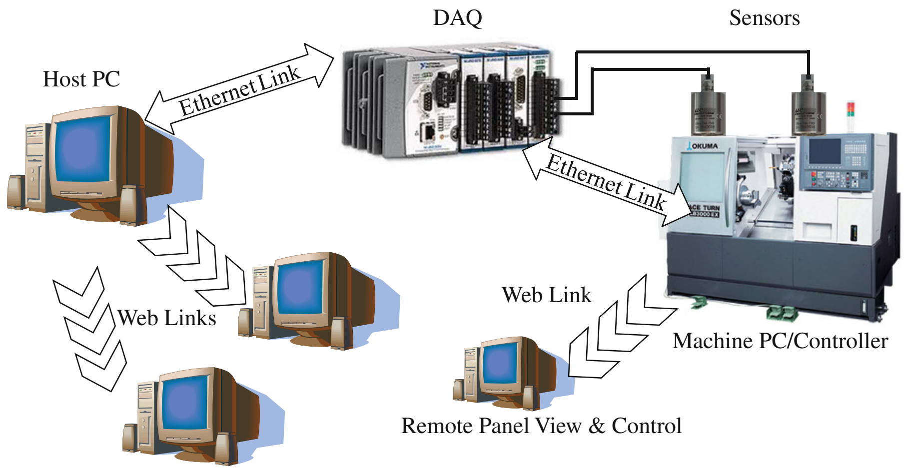
Abbreviations

CBM	Condition based maintenance
DAQ	Data acquisition
CNC	Computer numerical control
COTS	Commercial-off-the-shelf
OAC	Open architecture control
API	Application programming interface
FFT	Fast fourier transform

A typical CBM system: components and architecture

A typical computerized monitoring system usually consists of four main components: sensors, a microprocessor or data acquisition system (DAQ), a host computer, and software program(s) (Mobley 1990). The sensors would allow for signals to be acquired via the DAQ. These signals would then be sent to the host computer and be processed through its designed software program(s). The software programs should allow for the machine health and its conditions to be determined as well as providing prognostics to help decide maintenance actions (Thurston 2001). Technological advances have allowed these type systems to be much more flexible. Signal processing can be performed on a host computer (Mobley 1990), as well as by a central server (Korn 2010). The use of a central server allows for multiple parties to view data on the same network or over the internet. Data can even be transmitted to the DAQ components via wireless sensors (Thurston 2001; Jemielniak 1999; Elshayeb et

Fig. 1 CBM System architecture for a CNC machine



al. 2010; Tiwari et al. 2004). A system schematic including many of these components discussed is shown in Fig. 1.

Integration of CBM systems with machine control: current picture

A computerized CBM system from a machine's original equipment manufacturers' (OEM) perspective allows for maintenance to be built into the machine which provides many benefits. Because of a single user interface (i.e.: CNC control panel), alarms and flags can be raised and brought to attention of the user. If the alarm is of catastrophic consequence, it can be made to shut the machine off until maintenance can be carried out, thus promoting longevity of the CNC system as well as the safety of its operators. An integrated CBM system can also serve as a feedback of performance of the product which can aid in improvements in the future design (Ahuja and Khamba 2008). This allows for both corrective maintenance and maintenance prevention strategies to be employed as well as CBM, adding to the system's capability and effectiveness (Jardine et al. 2006).

While there are computerized CBM systems currently available on the market, such as the Predator system (Predator Software Inc. 2010), GE's Bently Nevada Continuous On-line Monitoring Systems (General Electric Company 2010), and InCheck Technologies' InSite remote condition monitoring system (Korn 2010), the use of these commercial systems are not continuously seen throughout the manufacturing industry. This may be because of a general monitoring system cannot serve the specific need of a particular company or operation. Academic research is also being carried out to help advance and improve monitoring systems, yet its impact on industry has been limited (Matsubara and Ibaraki 2009). An XML based CBM software has been developed for the aircraft manufacturing (Joshi et al. 2012). This lack of commercial system usage in industry can be attributed to different causes. They are:

- Difficulties with commercial-off-the-shelf (COTS) products integrating properly into machines
- Proprietary interfaces
- Software performance and flexibility issues (Thurston 2001)
- Costs of the sensors and sensor installation
- Insufficient understanding of the benefits a system such as this can provide (Matsubara and Ibaraki 2009)

Before trying to tackle the sensor costs and lack of benefit understanding, the first three causes can be offset by employing an architecture system that supports both event-based and time-based data processing and reporting. This is the main motivation behind the work covered in this paper. Utilization of an open architecture system would allow for these issues to be efficiently overcome.

OAC—the most fundamental requirement

As observed by Matsubara and Ibaraki (2009), the application of intelligent control techniques in an industrial environment is majorly inhibited because of proprietary controls by machine tool manufacturers. The control algorithms developed by these manufacturers are not made to be altered by engineers who wish to enhance the performance of the machine tool outside the machine tool manufacturing organization. However, with the European initiative for the open system architecture for controls within automation systems (OSACA) in 1992, development of an "open" architecture control system was sought (Brecher et al. 2010). Open architecture control (OAC) was born from this initiative. OAC provides the possibility to access a machine's internal data as well as have the ability for more user control in a machine's movements.

State of the art open control systems include Sinumerik 840D from (Siemens AG 2010), IndraMotion MTX from (Bosch Rexroth AG 2010), and the TwinCat system from

(Beckhoff Automation 2010). Sinumerik 840D works on the structure of object oriented NC kernel developed in C++. IndraMotion MTX provides users with the possibility of integrating their own jobs built in the C language. TwinCat uses the Microsoft's Visual Basic.NET framework for the programming of their devices.

Advantages of OAC systems are being leveraged for online measurement, report generation and remote viewing of the production capacity of CNC machines. Note that it also allows for possible integration of external sensing and control systems. The fundamental work of this paper is leveraging this capability for integrating a CBM system into a machine control.

CBM system architectures under investigation

Implementation of the CBM system: fundamental challenges

The core of this work is the research performed at Clemson University's International Center for Automotive Research (CU-ICAR) devoted to developing and enhancing automated monitoring and maintenance systems for CNC machines. This is possible by employing a machine control that supports an OAC structure.

A variety of different machine parameters (coolant concentration, coolant pH, spindle bearing condition, spindle vibration, and spindle temperature) have been investigated, allowing for the CBM systems to provide data in multiparameter measurements. This sensor fusion enables a more holistic approach to understanding a CNC machine's health. Operators and engineers can now be more informed, allowing for maintenance repair work to be planned and implemented before an unexpected breakdown or catastrophic failure occurs.

For this research, Okuma machine tools were utilized for this application development. Okuma machines are equipped with their own OAC machine controller, named the THINC OSP. The OSP is essentially a Windows PC mounted on the backside of a numerical control (NC) real time PLC. Being a Windows based system, applications can be written in the Visual Basic.NET (VB.NET) framework to run software programs directly on the control. This provides the ability to (1) control the machine's movements (in a limited sense) and (2) extract desired data from machine parameters at appropriate times. A VB.NET application can be created to communicate with the machine's application programming interface (API) to take advantage of these abilities. Data such as spindle speed, current part program, and current tool selected can be gathered via the API. The API also allows for the feedrate to be controlled; however, control signals for the spindle motor and turret still remain inaccessible.

Three different systems (applications) were developed, each providing different ways to interpret sensor signals on the machine control. However, during the development of these systems, proprietary interfacing was found to be a major problem in a system's ease of development and sensor/software integration. Four issues arise due to this proprietary interface problem on the Okuma machines being utilized:

- The DAQ software is be unable to communicate with the VB.NET application.
- If communication is possible, at least two pieces of software (DAQ software and an API application) are needed to run on the machine, which could lower the machine controller's performance.
- DAQ software licensing fees could cause the system to be more expensive, as each machine will need one.
- The types of sensors used in the proprietary systems are a limiting factor in system customization as only certain sensors can be used with certain interfaces.

The systems discussed get around these issues by using open architectures. The summary of all the three applications is presented in Table 1.

Architecture 1: independent CBM sensing and control unit [22]

The CBM system in Architecture 1 was developed as a proof of concept. This type of architecture is mostly utilized in the CBM programs in current industry. As shown in Fig. 2, it features a DAQ and control unit that works independently of the machine controller. Most of the third-party CBM systems follow this architecture. The advantages of these types of systems include separate control and sensing of the vital signals, high sampling rate, and software and hardware platform independence.

As a demonstrative prototype system, coolant temperatures and a spindle vibration signature were recorded for an Okuma LB3000EX CNC lathe (refer to Fig. 3). The vibration signature was then processed to produce a frequency response chart with the help of external sensors and DAQ system. With the sampling rates as high as 1 MHz, the system demonstrated the capability of capturing the onset of tool chatter.

The frequency response chart shows the frequency harmonics associated with the machine tool's spindle as shown in Fig. 4. Tool chatter conditions were generated to demonstrate the fast fourier transform (FFT) algorithm used. During the chattering phenomenon, a shrill audible noise could be heard and the frequency response of the accelerometer indicated a peak at a high frequency, circled in Fig. 4. As soon as the shrill noise subsided, indicating that there was

Table 1 Discussed CBM architectures summary

Architecture and application	Connectivity	Hardware details	Software capabilities
Architecture 1: Machining chatter detection and coolant temperature monitoring	Stand alone controller and DAQ system monitoring without communicating with CNC control	Controller and DAQ: cRIO 9022 control prototype (National Instruments Corporation 2011)	Monitoring of spindle vibration data in time and frequency domain
		Sensors: Kistler 8722A accelerometer, Omega K type thermocouples	Monitoring of temperature data in time domain
Architecture 2 (Application 1): Okuma coolant monitoring system	OAC PLC/DAQ integrated into the CNC control	Controller: Okuma OSP	Monitoring of coolant concentration and pH
		DAQ: Beckhoff TwinCat PLC (Beckhoff Automation GmbH 2011)	Instantaneous and historical data
		Sensors: Atago CM-780N Brix concentration meter (Atago U.S.A., Inc. 2011) and Sensorex S600CD pH probe (Sensorex Corp. 2011)	Generation of alerts
Architecture 2 (Application 2): Okuma spindle monitoring system	OAC PLC/DAQ integrated into the CNC control	Controller: Okuma OSP	Monitoring of spindle bearing condition
		DAQ: Beckhoff TwinCat PLC	Instantaneous and historical ultrasonic sensor data
		Sensors: Ultra-Trak 750 ultrasonic sensor (UE Systems Inc. 2010) and Okuma J type thermocouples	In process measurement or test modes
			Uploading of data to ConstantCare^{TM} website for remote viewing

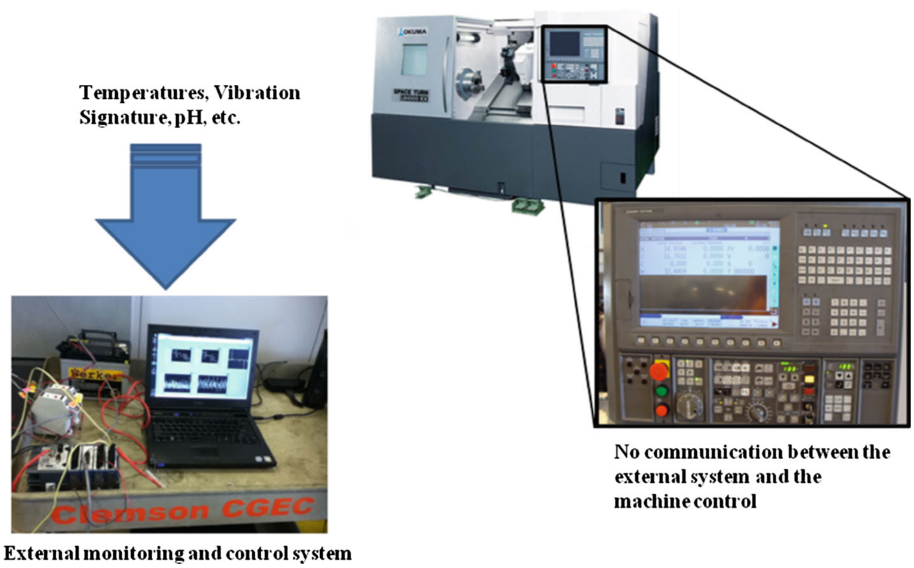


Fig. 2 Schematic representation of architecture 1

no chattering, the peak reduced almost instantaneously. This verified the peak around 1,500 Hz was indeed the chattering frequency which was being observed. Investigating this phenomenon reinforced the capabilities of the DAQ system being utilized.

The prototype system of Architecture 1 shows the potential of what open architecture capabilities allow to be accomplished. However, if a commercial system was to be realized, several items would need to be addressed, mainly hardware and licensing costs. To provide a CBM system as a possible stock option that can be purchased with the machine tool, the overhead costs would need to be reduced. While the hardware/software package used in this experiment allows for a CBM system to be very flexible, it was a bit too expensive, costing upwards of $4,600 in DAQ hardware alone.

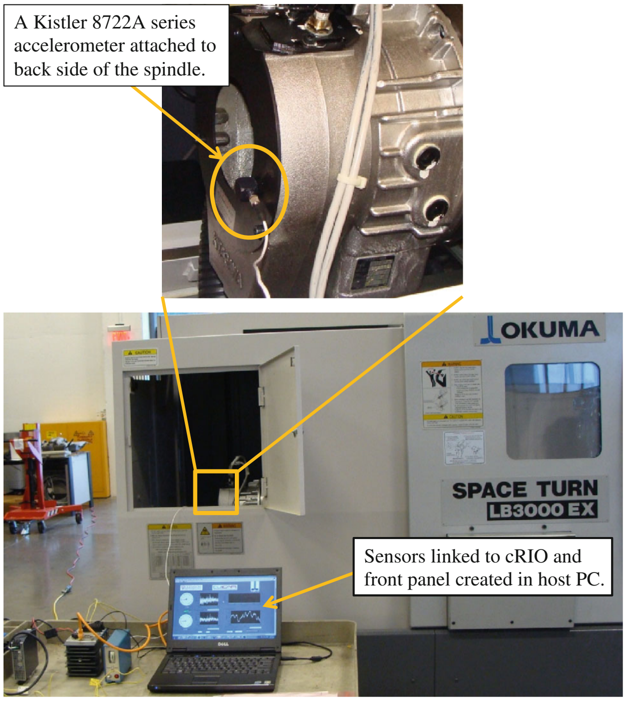


Fig. 3 Experimental set-up for the monitoring system demonstration

Architecture 2—application 1 coolant monitor

Okuma, as well as other companies, are now developing applications for the Okuma OSP. This application focuses on an application developed by Okuma America Corp. that monitors a machine tool's coolant health, named *Okuma coolant monitor*. The system monitors the concentration and pH for the coolant from the machine control (even while the machine is operating). These two parameters were chosen as they are the most important indicators for coolant condition (Martin and Thorpe 1990; University of Minnesota 2004; Methods & Equipment Associates 2001).

One limitation with this application is that it does not use any of the API features that are provided with the machine. This limits the amount of information that can be passed from the machine to the engineer. For example, if the pH of the coolant increases suddenly, the direct cause may be unknown. However, the API utilization would allow for a part program history to be recovered and may be able to inform the engineer that the pH changes only when Part X is machined, indicating that the parts are dirty entering the machine. This provides the possibility of taking a process issue (based within the confines of the machine) and being able to expand it to a system level problem. Once these "dirty parts" are identified, issues in the upstream process can start to be identified.

Architecture 2—application 2: spindle monitor [26]

Using Architecture 2 as an example of connectivity desired in an industrial system, an application for Architecture 2 was developed to investigate spindle health monitoring. The system is comprised of sensors, data acquisition devices, and interactive software to monitor spindle health. It is has been designed to supply a single quantifiable number for spindle bearing condition. The sensors are all non-invasive, allowing for the machine's major components to be kept the way they are currently designed. Figure 5 depicts the schematic representation of this application.

The main software program, composed in the VB.NET framework, allows the user to choose how the monitoring is performed: in a test mode or as an in-process measurement. Regardless of which mode selected, the user will be able to see the machine's current spindle state as well as see the past data on the spindle via history trending. This data can also be viewed remotely from an internet-based application. It is important to note here that the software programs runs on the machine controller, demonstrating complete connectivity with the machine system architecture.

System validation and testing [26]

Condition based maintenance (CBM) system validation and testing was performed on an LB3000EX lathe at the manufacturer's partner teaming facility. Figures 6 and 7 show the system setup on the machine. To allow for the same data acquisition hardware to employ both the *Okuma Coolant Monitor* as well as the *Okuma Spindle Monitor*, an additional analog current module was added to the PLC and the

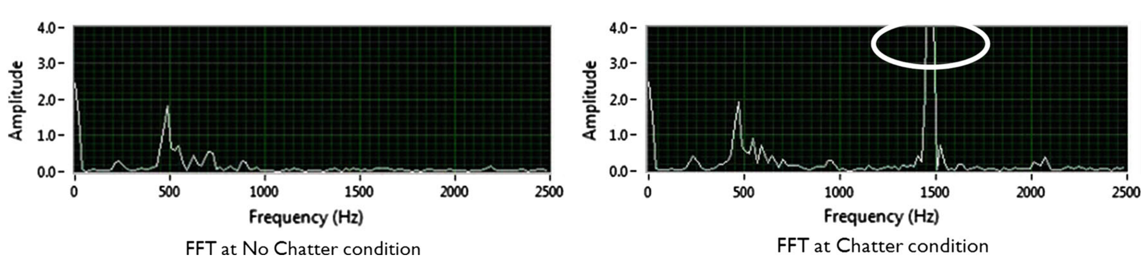


Fig. 4 Frequency response of the spindle under chattering and non-chattering condition

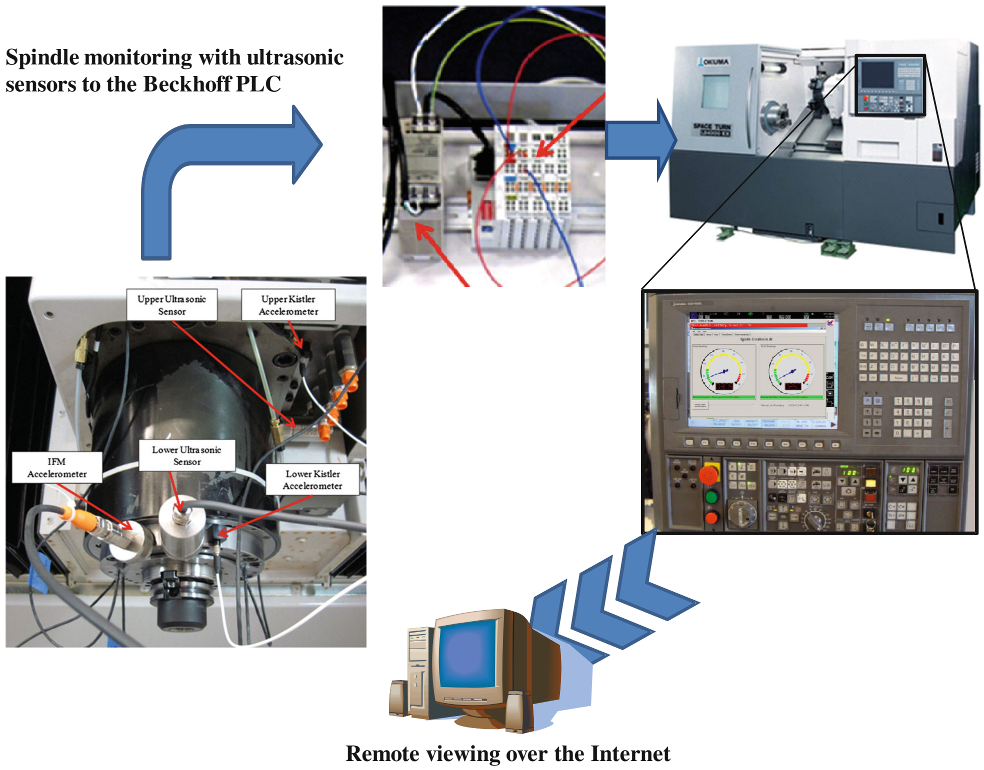


Fig. 5 Schematic of architecture 2 application 2

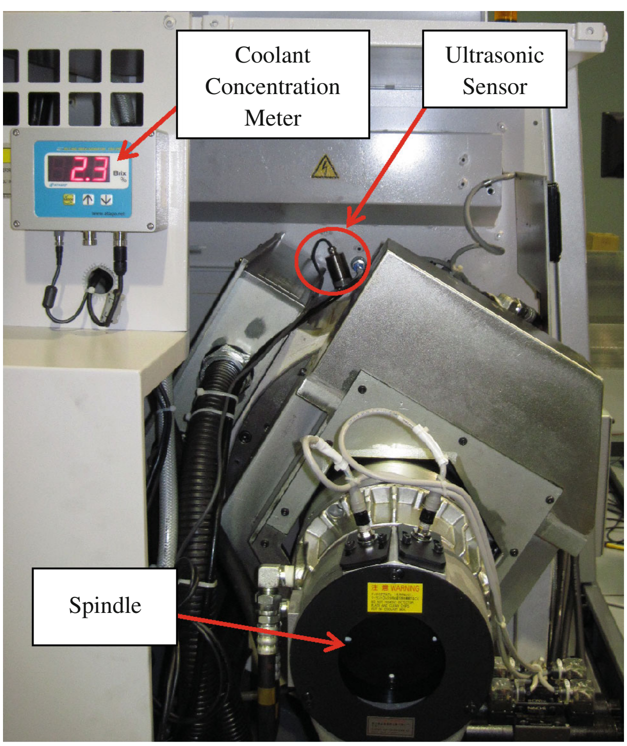


Fig. 6 Ultrasonic sensor placement on the LB3000EX for imX (utilization of two CBM applications on one machine)

Fig. 7 Software loaded onto the machine control

software program modified. This served as a verification that both systems could be run from one PLC.

In addition to ensuring the application would function properly on the machine control, the system needed to be tested to ensure that the onset of a spindle bearing failure could be detected before the spindle actually failed. Therefore, a test protocol was developed for an accelerated life test on an Okuma machine (MU 500 VA 5 axis vertical machining center) spindle, where a brand new spindle was run until bearing failure occurred. This helped to gain a better understanding of (1) the system's ability to detect a spindle problem and (2) what actually happens to a spindle throughout its life as it degrades for various spindle related failures. The accelerated testing was meant to simulate possible sources for spindle failure, all of which have been common problems that are seen in the field.

Testing protocol and results

The testing to be performed was listed in order of execution in Table 2, with each successive test providing a greater amount of spindle bearing damage than the last. The spindle was taken through a variety of actions in order to gather as much data from each of the "incidents" as possible. The running speed chosen for this test is 9,000 RPM as this is the spindle speed with the most amount of ultrasonic sensor excitation. This indicated that this RPM was somewhere near the spindle's natural frequency.

Unfortunately, the test spindle failed during Test B—Improper (or lack of) Lubrication. However, valuable insight was gathered. Figure 8 shows how ultrasonic and temperature measurements coincide with a resin cage bearing failure at 9,000 RPM (the spindle speed for which the spindle was baselined at). The figure shows that once the spindle speed reached 9,000 RPM, the ultrasonic sensor read its baseline value (0 dB) as indicated in the figure. After about 7 min, there was a sharp spike in the ultrasonic reading, indicating the failure. However, the ultrasonic level only came up from the original baseline by 5 dB. This is below the 8 dB microscopic damage threshold. According to the dB scale, an increase in 7 dB is only a 2.2 time sound increase, much

Table 2 Testing procedure

Action/test	Description	Length of test/event occurrence
A	Establish a baseline	3 h
B	Induce an improper lubrication condition	Temperature of 60 °C or an 8 dB increase from baseline
C	Establish a proper lubrication condition	3 h
D	Induce a coolant contamination condition	1 week
E	Induce powder contamination condition	TBD
F1	Light Brinelling of spindle bearings	1 week
F2	Medium Brinelling of spindle bearings	1 week
F3	Heavy Brinelling of spindle bearings	Complete bearing failure (machine shutdown)
G	Root cause analysis of bearing failure	N/A

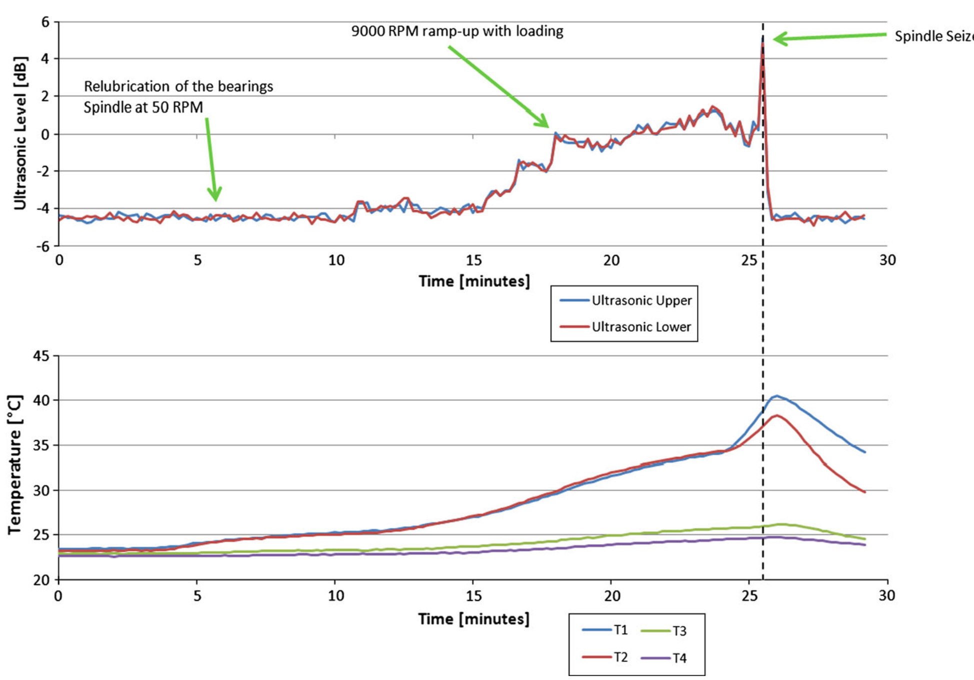


Fig. 8 Ultrasonic and temperature measurements for a resin bearing cage failure (Martin and Thorpe 1990)

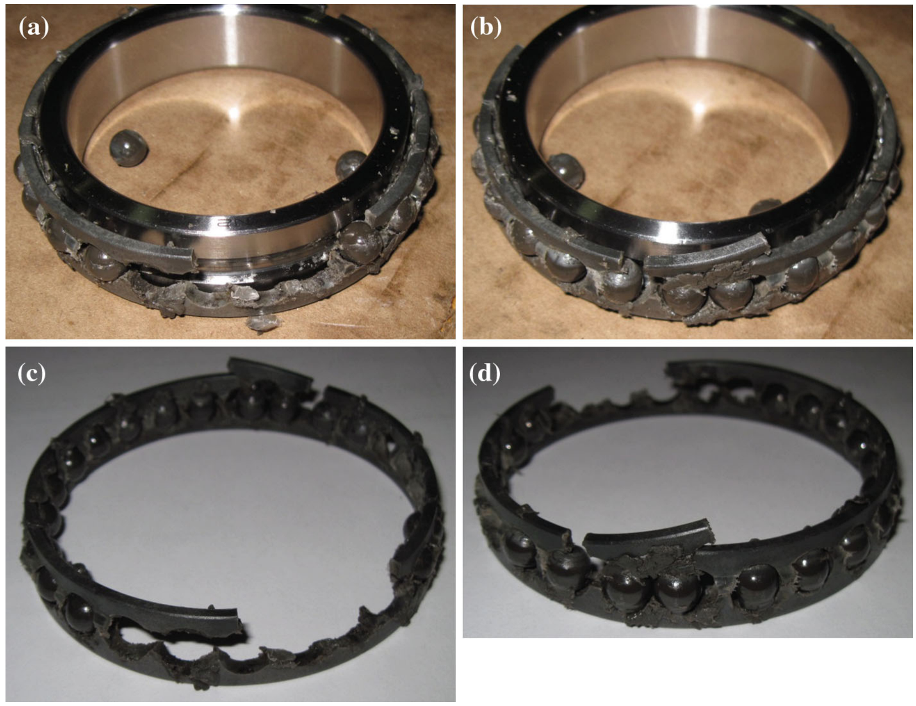


Fig. 9 Cage damage (Werner 2011)

less than the 56 time sonic amplitude increase that is associated with a bearing failure at 35 dB. With this being said, the ultrasonic sensor may not be able to detect a cage failure (of this resin material) until it is too late. This is most likely because the sounds leading up to a plastic cage failure would be much lower than the 35–40 dB range, as opposed to a metal cage that was degrading.

The temperature graph tells a different story. It was not noticed during testing, but as the machine was being relubricated, the temperature started to increase, even at the 50 RPM speed. Around the 25 min mark, the temperature for the lowest two bearings (where the load was being applied) started to increase more rapidly as the ultrasonic reading decreased (just before the spike). Thirty seconds later, the maximum temperature for lower bearings reached 40.5 and 38.3 °C respectively after the spindle was stopped. A dotted vertical line stretching across both graphs has been used to allow for this to be seen more easily.

This test shows the value in having multi-parameter measurements. The interesting outcome here is that the ultrasonic sensor was not able to detect the resin cage failure until the failure had already occurred. However, pairing the ultrasonic measurement with a temperature measurement allows for a multi-parameter set of information to be understood. The ultrasonic sensor alone is not the end-all-be-all sensor measurement for bearing failure. The ultrasonic sensor can detect issues before temperature or vibration really becomes a factor (National Aeronautics and Space Administration (NASA) 1972), however, in this case, it was not (due to the resin cage degradation not being loud enough/in the ultrasonic range) (Fig. 9).

Relative comparison of architectures and summary

Development and deployment of different CBM architectures brought to light the salient challenges that need to be overcome to promote widespread usage of CBM system in manufacturing industry. Table 3 indicates the relative merits and demerits of the architectures investigated. All the architectures have characteristics in favor or against of their selection based on the need of a particular application.

Intelligence in CBM systems

After discussing various CBM system architectures, this section presents the ongoing research work helping to advance the OAC CBM systems. With these basic tools, there are opportunities to extend role of the sensor systems from just raising flags to the role of decision support systems. It is important to mention the efforts taken by (2002) in this area. As a result of the program, many intelligent monitoring applications were demonstrated (Ni and Djurdjanovic 2003). It's important to note how this work differs from the work reported. This research aims to integrate the machine control with the external Data acquisition and control hardware and software, which is not the case in former works cited.

Table 3 Relative comparison of CBM architectures discussed

Architecture and application	Customization	Data accessibility	Sampling rate	Cost
Architecture 1: machining chatter detection and spindle temperature monitoring	*High*—LabVIEW allows complete customization of application	*High*—Complete accessibility to all the signals in real time	*High*—relative to PLC system, this prototype system provides high sampling rate	*High*—due to control prototyping system, software licensing
Architecture 2 (application 1): Okuma coolant monitoring system	*High*—VB.NET Windows based application	*Low*—DAQ side has high accessibility, but CNC side limited due to no API	*Med*—limited by the Windows application and PLC DSP	*Med*—high sensor costs, but low hardware costs
Architecture 2 (application 2): Okuma spindle monitoring system	*High*—VB.NET Windows based application	*Med*—DAQ side has high accessibility, but CNC side limited by API options	*Med*—limited by the Windows application and PLC DSP	*Low*—low sensor and hardware costs

Extension of additional sensors to decision support system

The commercial CNC systems available today are loaded with sensors to monitor and control the individual systems; these include the temperature sensors for electrical cabinet, oil pressure sensors for lubricated guide ways, temperature sensors for headstock cooling unit, etc. (Peng et al. 2010). As discussed in the current work, the accelerometers and ultrasonic transducers can be integrated into the machine control. During the discussion of results of the spindle lack of lubrication test, it was mentioned that both the ultrasonic transducer response and the spindle temperature response indicated an impending spindle failure. However, in this specific case, a temperature rise was initiated before an increase the in ultrasonic emissions could be detected. Through the use of this sensor fusion, the role of sensing systems can be extended to decision support systems. Thus, the role of a CBM system rises from regular monitoring (i.e.: diagnostic) to a prognosis system. A diagnostic system will simply raise flag about state of the system ("normal" or "fault"), a prognostic system on the other hand will provide information about how much time the machine can be operated before catastrophic failure. For example, consider a condition monitoring system for CNC machine. A diagnostic (only) system will raise an alarm in case of excessive bearing vibration (or temperature) indicating that it is unsafe to use the machine anymore. A diagnostic and prognostic system will not only indicate the impending failure, but also indicate the time machine can be used (even at reduced operation limits) before the part has to be completely changed. This becomes excessively important in case such alarm is raised during the machining of the part, and part is too costly to salvage (e.g. machining of power generation turbine blade or machining of aircraft wing section).

One of the widely used techniques for CBM decision support system is based on Statistical approaches. Other approaches to signal classification include artificial intelligence (AI) techniques and model based diagnostics and prognosis techniques (Jardine et al. 2006). In AI techniques, artificial neural networks (ANN) are used to model the response of the system from known inputs by extensive model training (Schalkoff 1997). ANN has been applied to equipment bearing condition monitoring and remaining useful life (RUL) calculation recently (Tian 2012). Proportional hazards models (PHM) is also one of the methodologies for RUL calculations. PHM analysis is based on the hazard function and failure probability models, and expected failure rate is derived by maximization of the partial log likelihoods (Bajnevic and Jardine 2006). Model based approaches include statistical modeling of the process characteristics and extraction of fault feature. This fault feature then becomes the signal that needs to be classified in "safe" and "unsafe" classes (Li et al. 2012). The accuracy and robustness of different approaches have been compared (Orth et al. 2012). In current work, it was noticed from the baseline test that observing the sound signature (ultrasonic transducer reading) of the good spindle falls very closely to that of a resin cage bearing failure. This provides the need for the formulation of a probabilistic approach in failure prediction. In this paper, a statistical approach is pursued involving signal classification using Bayesian Naïve Classifier, relevant theoretical background and numerical simulations follow in following sections.

Decision theory

Decision theory is a mathematical framework for choosing actions in light of uncertainty (Bernoardo and Smith 1994). The fundamental problem of decision theory can be described as a situation where one would be required to take action when presented with data that contains uncertainty. Each action has its own set of consequences. The desirable consequences can be considered as a profit whereas the consequences that are detrimental can be considered as loss. The mathematical problem of making a choice is then to take

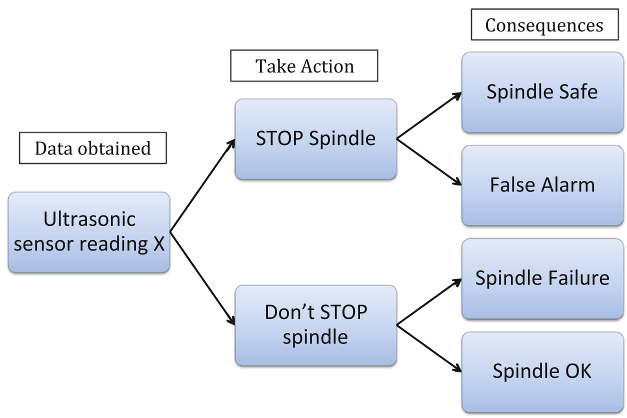


Fig. 10 Decision process for a CNC spindle health monitoring

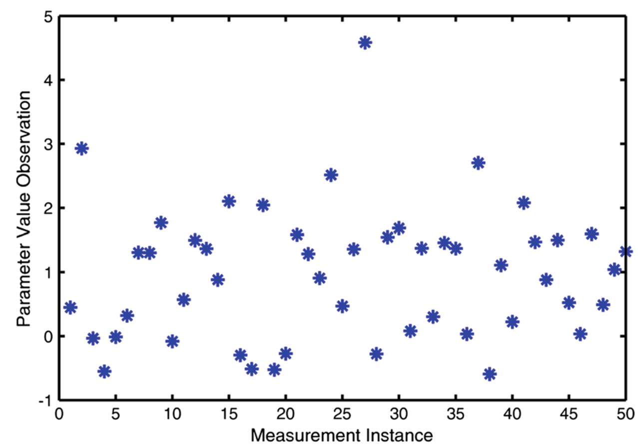


Fig. 11 Bayesian parameter inference: noisy data

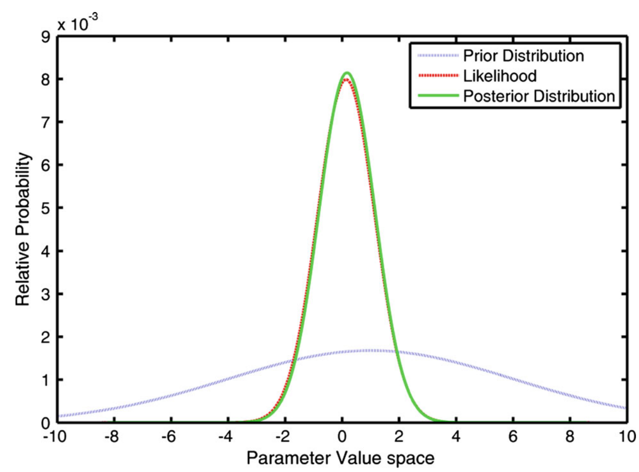


Fig. 12 Probability distributions for prior, likelihood and posterior beliefs for parameter value after single update

action in a way such that the profits are maximized (or losses minimized). This process is graphically explained in Fig. 10. Upon receiving an ultrasonic sensor reading value of X dB, the controller is faced with two choices: STOP Spindle and Don't STOP Spindle. Upon stopping the spindle, the controller might have either saved a failing spindle or raised a false alarm. At the same time, not stopping the spindle may lead to either failure of the spindle or the spindle would keep on running without any problems.

The question that arises from this is of course: What is the best decision to take when a signal is received? The two most commonly used theories to formulate this question mathematically are utility theory and Bayesian decision theory. The focus of this work is on the Bayesian approach, therefore the fundamentals of the Bayesian perspective of probability will be discussed as well as how Bayesian decision theory can be applied to answer the question at hand.

Bayesian theory of probability

In its simplest sense, a Bayesian view of probability indicates the state of knowledge or belief in a certain hypothesis (Bernoardo and Smith 1994). In context of parameter identification, let ω, be the parameter of interest, K be initial state of knowledge, D be the data point, Bayes' theorem can be written as follows:

$$p(\omega|D, K) = \frac{p(D|\omega)p(\omega|K)}{\int p(D|\omega)p(\omega|K)d\omega} \tag{1}$$

In Eq. (1), $p(\omega|K)$ is read as "the probability distribution of value of parameter ω, given initial state of knowledge K" often referred to as a "prior". $p(D|\omega, K)$ is read as "the probability that the data point observed would relate to the parameter value", called the "likelihood". Likelihood often relates the data point to the parameter of interest via a model. Hence, it is a very important part of the solution which will be observed in later sections of this work. Finally, $p(\omega|D, K)$ is the probability distribution of value of parameter ω, given initial state of knowledge K and having observed the data point D, called a "posterior". The denominator is a normalization factor, since the probability distribution must sum to unity.

To demonstrate the Bayesian inference to extract the true value from set of noisy observations is discussed. Consider Fig. 1, where 50 observations for some parameters have been made from a set of experiments. Desired is the estimated value of parameter that matches the true value. One starts with prior distribution—the initial belief in the value of the parameter, which is modeled by a Gaussian distribution with zero mean and large variance. The likelihood function indicates the degree of belief in measurement (measurement error) and from that, the posterior distribution of parameter value is obtained. Since the sum of probabilities should be unity, the probability functions related to prior, likelihood and posterior are normalized (Fig. 11).

Figure 12 shows this process graphically. Few points are worth noting, the posterior distribution has much less spread as compared to the prior. The definitiveness of both prior and likelihood also dictate the variance of the posterior. After single update, the spread (variance) of posterior distribution of parameter has reduced greatly. As more and more observations are obtained, the posterior distributions can be updated. In a sequential data processing setting, the prior for next update will be replaced by current posterior distribution. Furthermore, the prior can be uninformative (uniform distribution), thus showing complete ignorance about the value of the parameter, where the likelihood dominates the posterior behavior if this is the case.

In Fig. 13, the probability distributions are shown for after 5 and 50 updates. As more data is obtained, the variance of posterior distribution reduces, indicating that the belief in value of parameter is stronger. The parameter estimate value is obtained by finding the most probable value of posterior- which is called maximum-a posteriori (MAP) estimate (Sivia 1996). Figure 14 shows the MAP estimate from the data. The true value of parameter (1.00) is shown with red line. As it can be observed, with more updates, the confidence in value of parameter is higher and converges to true value of parameters.

Naïve Bayes classifier theory

Fundamentally, the decision problem is to classify the signal as a "safe" or "unsafe" condition (Wilson et al. 2008). Let us denote the signal obtained from the ultrasonic sensor as x_U, and C_1 be the class that denotes a "safe" signal. C_2 is the class that denotes the "unsafe" signal condition. The general inference problem is calculation of $p(\mathbf{x}, C_k)$, which gives the most complete probabilistic description of the situation. As mentioned before, the class of the signal C_k given signal x needs to be determined. Mathematically the probability of this event is given as $p(C_k|x)$, and is calculated as follows:

$$p(C_k|x) = \frac{p(x_U|C_k)p(C_k)}{\int p(x_U|C_k)p(C_k)dx_U} \tag{2}$$

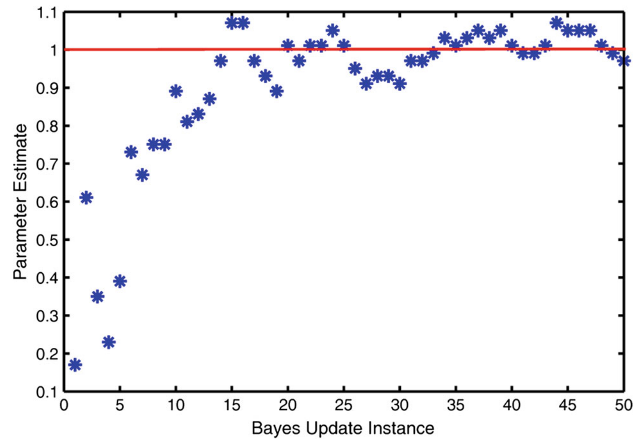


Fig. 14 MAP estimate of parameter value from noisy data (Color figure online)

Definitions of terms in Eq. (2) are given below:

- $p(C_1)$: Marginal probability of spindle being good (based on failure rates in field)
- $p(C_2)$: Marginal probability of spindle being bad
- $p(x_U|C_1)$: Probability of obtaining ultrasonic reading x_U, given the fact that spindle is good
- $p(x_U|C_2)$: Probability of obtaining ultrasonic reading x_U, given the fact that spindle is bad
- $p(C_1|x_U)$: Posterior probability of spindle being good given the ultrasonic reading x_U
- $p(C_2|x_U)$: Posterior probability of spindle being bad given the ultrasonic reading x_U

In many of the applications, the cost of misclassification is higher depending on which loss minimization algorithm is employed. Consider the loss matrix given in following equation.

$$L = \begin{bmatrix} 0 & 100 \\ 1 & 0 \end{bmatrix} \tag{3}$$

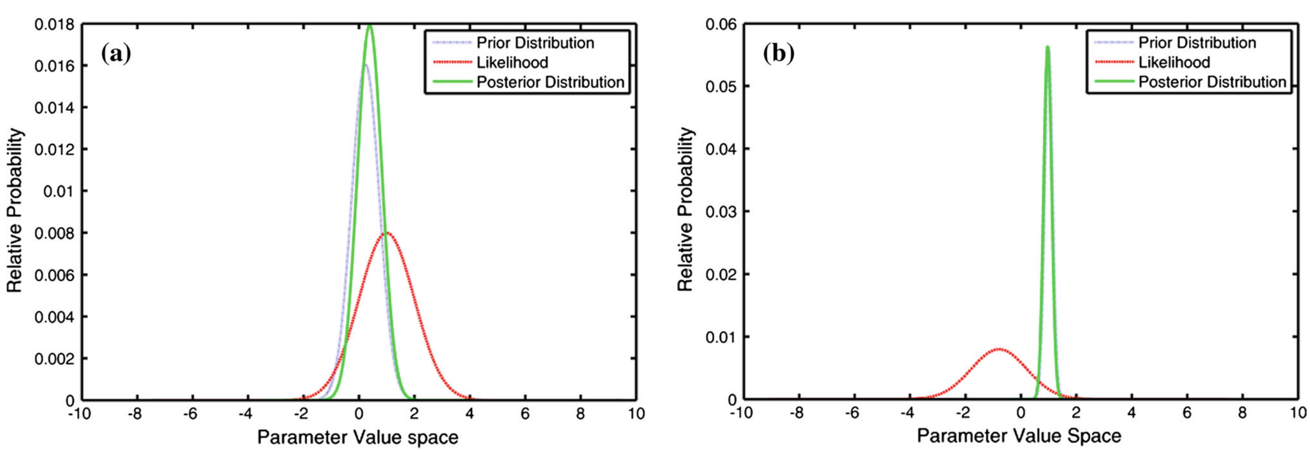


Fig. 13 Prior, likelihood and posterior distributions for parameter values for **a** 5 updates and **b** 50 updates

This means that the penalty of misclassifying to class C_2 is much higher than the class C_1. The reason for this is simply that misclassifying an unsafe condition to be a safe condition is much more severe than misclassifying a safe condition to be in an unsafe condition. This is also called the cost function, where the decision analysis goal is to take action so as to minimize this function. For a given input vector $\mathbf{x}$, the uncertainty in the true class is expressed via the joint probability distribution $p(\mathbf{x}, C_k)$. We seek to minimize the expected loss, given by

$$E[L] = \sum_k \sum_j \int L_{kj}\, p(\mathbf{x}, C_k) d\mathbf{x} \tag{4}$$

Using the product rule, the optimal decision rule that minimizes the expected loss is the one that assigns each new x to class j for which the quantity of Eq. (6) is a minimum.

$$\sum_k L_{kj}\, p(C_k|\mathbf{x}) \tag{5}$$

Note that this can be implemented once the knowledge of posterior distribution is available and becomes a routine task of using a gradient based search method or other optimization routines. In the next sub-section, the procedure of calculating the posterior is explained with pseudo-code and numerical experiments.

Numerical simulation: calculation of posterior probability

Based on the discussion above, the most important quantity to make decision is then calculation of posterior probability $p(C_k|x_U)$. Based on the destructive test results shown in "Extension of additional sensors to decision support system", we perform the calculation of posterior probability. The actual values used here are given as follows. The means, variances and distributions of the ultrasonic sensor were chosen from observing the data from the tests as discussed in ("Testing protocol and results"). From the experiments, sample baseline test data is shown (Fig. 15) with the accompanying probability distribution (using the Kernel density estimation). To test the normality, Kolmogorov Smirnov test was performed and it fails to reject null hypothesis at the 5 % significance level with p value of 0.6699 (proving that data is indeed normally distributed).

- $p(C_k)$: Probability of the event of spindle being good or bad (50 %)
- $p(x_U|C_k)$: Calculation based on baseline and destructive tests
  - $p(x_U|C_1) = normpdf(x_U, 0, 0.5)$
  - $p(x_U|C_2) = normpdf(x_U, 2, 0.5)$
- $\int p(x_U|C_k)p(C_k)dx_U$: Normalizing constant

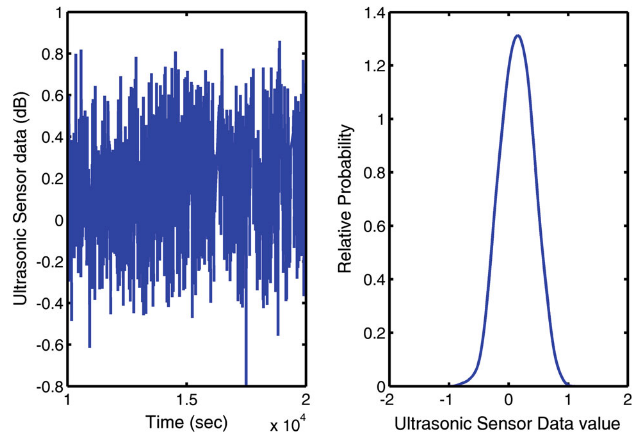


Fig. 15 Ultrasonic sensor data sample and probability distribution

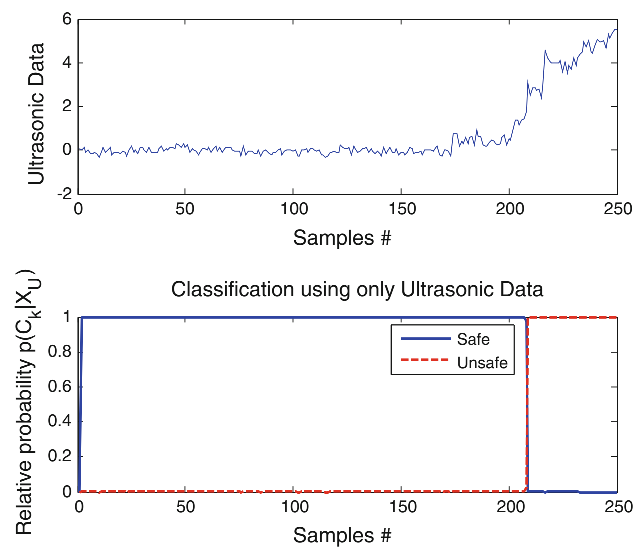


Fig. 16 Signal classification using ultrasonic data only

The top subplot in Fig. 16 shows the actual ultrasonic data observed during the destructive test on the vertical machining center, while the bottom subplot shows the posterior probability $p(C_k|x_U)$ at every signal sample observed. The following observations were made from the data produced:

- When spindle bearing begins to fail, the ultrasonic reading jumps up by a decibel (at around sample 180).
- Since spindle is not stopped at that point, it becomes a catastrophic failure showing a sudden jump in the decibel level and keeps going on towards the end of data collection.
- The relative probability plot (bottom subplot) shows the classification probability. The blue line indicates the event "Spindle Safe" while the red line indicates event probability "Spindle Unsafe". A point worth noting is that the earliest detection that can be made is at sample 210.

It was mentioned in "Extension of additional sensors to decision support system" that the temperature reading from the thermocouples started showing a positive trend before the ultrasonic sensor data reflected actual failure. In the next section, the idea of combining information from temperature data and ultrasonic data is investigated using sensor fusion.

Combining the models: sensor fusion

Sensor fusion has been used in distributed and centralized monitoring and control systems in wide variety of applications. It refers to using more than one (in numbers and types of) sensors to take a control action towards controlling the plant of interest. Fundamentally, having more than one sensor (or type of sensors) to gather feedback is done to provide (Henderson et al. 1998):

- Higher resolution in information (spatial and temporal)
- Robustness of sensing system
- Complementary information

Placing more than one thermocouple on the spindle at various places gives more spatial resolution of the spindle temperature. Sometimes, it is desired to have more sensors as a fall back option in case one of the sensor fails. A typical example is the electronic throttle body (ETB) unit inside a car's engine. For the position sensing of the valve opening, there are two potentiometers used, one as a backup sensor. Having more than one sensor to measure a quantity can also identify a fault in the sensor reading itself. In this case, there are four sensors measuring the temperature of the spindle. If one of the sensors is reading completely off the other three, it raises a red flag

As far as the current application is concerned, the fundamental question being asked is: "How can information be combined, in this case the spindle temperature and ultrasonic emissions, to predict a spindle failure before a catastrophic failure occurs?" An attempt is made to answer this question using the Naïve Bayes classifier (Bishop 2006).

The Naïve Bayes classifier works on the following principle, the true posterior of the spindle condition based on both temperature and ultrasonic data is given by

$$p(C_k|x_U, x_T) \propto p(x_U, x_T|C_k)p(C_k) \tag{6}$$

where:

- $p(C_k|x_U, x_T)$: Probability of the event "Spindle Safe/ Unsafe" given ultrasonic AND temperature data
- $p(x_U, x_T|C_k)$: Joint probability distribution of temperature and ultrasonic data given the class information

The fundamental assumption is this: The ultrasonic data and temperature data are independent of each other. In reality, they may not be independent, but we will see how this assumption makes the analysis easier to perform and yields results.

$$p(x_U, x_T|C_k) = p(x_U|C_k)p(x_T|C_k) \tag{7}$$

Thus equation can be rewritten as:

$$p(C_k|x_U, x_T) \propto p(x_U|C_k)p(x_T|C_k)p(C_k) \tag{8}$$

While the ultrasonic likelihood distributions $p(x_U|C_k)$ are used as before, the following distributions were used to calculate temperature likelihoods:

- $p(x_T|C_k) \sim normpdf(x_T, 25, 2)$
- $p(x_T|C_k) \sim normpdf(x_T, 28, 2)$

Figure 17 shows the actual data recorded in top two subplots, and in bottom subplots compares the classification probabilities when using only ultrasonic data versus using temperature and ultrasonic data. Following inferences can be made from this information:

- Temperature at the nominal (safe) condition is normally distributed around 25 °C with some standard deviation. When the spindle bearing starts to fail, it shows signs of failure early on in the temperature plot as the temperature gradually start increasing.
- For the same reason (an increase in temperature), the classification probability starts shifting from safe to unsafe region as early as from sample #175, the permanent shift is observed at sample #190.

It is important to note that the unsafe spindle condition is identified 30 samples ahead of time as compared to only observing ultrasonic data; this corresponds to 3.33 min in real time. When a machine is close to a failure occurring, 3 min can be crucial in terms of machine and operator safety. Mostly, the sensor fusion data techniques are used for the machine condition diagnosis and prognosis. This work leverages the sensor fusion with probabilistic decision analysis tools such as Naïve Bayes classifier.

Validation in industrial scenario

It is important to discuss the validation of such decision support system in light of implementation to industrial CNC systems. One could argue, that based on a single destructive test one cannot draw conclusions about the average life span of the spindle. The reliability models (based on statistical approaches) estimate the remaining useful life of the component based on statistical data and physics based models (Bajnevic and Jardine 2006; Stringer et al. 2012). In the present scenario, not only the magnitude of the ultrasonic sensor but also the rate of change with respect to time and

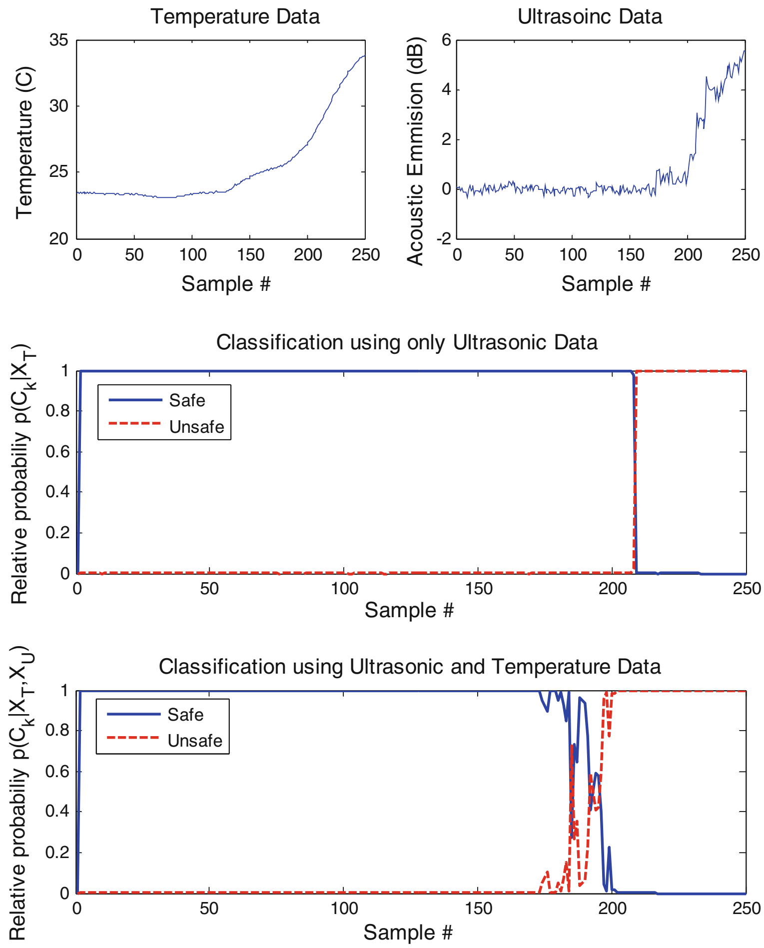


Fig. 17 Naive Bayes classification using temperature and ultrasonic data

corresponding temperature change was taken into consideration to make a decision. This test could be repeated many times on many spindles, but the fact that seizing of spindle would raise the temperature of bearings will not change. Of course, it is not possible to deliberately fail CNC spindle(s) for sake of building a model owing to cost and time constraints. That being said, authors are currently pursuing to implement the condition monitoring system in a real industrial scenario as a benchmark and observe the effectiveness in an industrial environment. With use of Bayesian statistical framework, the models can be learned in process, better reliability estimates can be made.

Conclusions and future work

In this paper, the challenges in integration of automated CBM systems with a CNC machine control were investigated by the development of various CBM applications. Different architectures investigated included an external monitoring and control system having no connection with CNC machine control (Architecture 1) and a PLC-DAQ based monitoring system integrated with machine control. Following these architectures, three applications were investigated: machining chatter detection (Architecture 1), coolant monitoring system (Architecture 2), and spindle monitoring system (Architecture2). The spindle monitoring system was validated by performing a destructive spindle bearing test which resulted in a spindle seizure due to lack of lubrication. The data gathered during the failure provided valuable insights in developing a framework for intelligent CBM systems. On the basis of Bayesian Decision Analysis and the Naïve Bayes Classifier, the numerical exercise performed shows the applicability of the algorithm for CBM systems. It was also observed that combining data obtained from the ultrasonic sensor and thermocouples could provide an even better spindle health indication than with just an ultrasonic sensor alone. With a foundation now provided, various directions can be pursued:

- Continued research in the establishment of safe and unsafe ultrasonic and vibration limits for an Okuma machine
- Effect of machining load on a spindle's ultrasonic readings [continued from (Werner 2011)]

- Generation of data based and physics based models for better inference on spindle condition.

It is also important to note the deployment costs of the various CBM architectures. This cost can become very advantageous to the end user. A few thousand dollars towards a predictive and preventive maintenance monitoring solution can prevent tens-of-thousands of dollars in lost production and unnecessary maintenance costs if the system is utilized as intended.

The use of CBM systems on CNC machine tools is not a recent development. The fundamental challenges involved in allowing for these systems to become more wide spread include the lack of accurate modeling of spindle failures, cost justification, cost of hardware/software, and finally seamless integration into a machine control. Though this work does not promise to solve all of these issues, but surely provides a firm step in the right direction.

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