Estonian Journal of Engineering, 2011, **17**, 1, 4–16 doi: 10.3176/eng.2011.1.02

In-process determining of the working mode in CNC turning

Tanel Aruväli, Risto Serg, Jürgo Preden and Tauno Otto

Department of Machinery, Tallinn University of Technology, Ehitajate tee 5, 19086 Tallinn, Estonia; tanel.aruvali@ttu.ee, risto.serg@dcc.ttu.ee, jurgo.preden@ttu.ee, tauno.otto@ttu.ee

Received 18 October 2010, in revised form 11 January 2011

Abstract. Autonomous embedded computers that form a sensor network can be applied in various fields. In the domain of industrial manufacturing, sensor networks can be employed for detecting events or phenomena of interest at the shop floor. Sensor network nodes collect and process data, transmitting sensed and fused information either to a central database or directly to the handheld computer, used by the production manager. Smart dust can be used at CNC machine tools for measuring vibration, noise and other essential parameters. These parameters can give a signal for unsuitable cutting conditions. Implemented experiments were made using wired solutions, but wireless solutions are proposed. The proposed solution helps to detect changes in shop floor and predict possible problems, thus avoiding unplanned pauses in production. It is shown that different working modes can be detected using in-process monitoring.

Key words: smart dust, wireless sensor network, manufacturing, e-diagnostics, in-process monitoring.

1. INTRODUCTION

High utilization and fault detection of metal working machinery is an issue of high importance in industrial applications. Operation in an undesirable mode can cause poor production quality, perversion of the material but also in extreme cases tool failures and damages to the machinery. Two of the last damages are especially harmful for production, causing unplanned breaks in production and delays in fulfilling customer orders.

The process of developing metal working machinery is ongoing. Building up more sophisticated working processes, using wear resistant tool materials, raising speeds and powers permit the production of more complicated parts and also shorten the time of machining. The increased efficiency and speed of production may also result in faster changes in the manufacturing equipment state – the step from the regular working process to an unstable condition is potentially also shorter. As a result, the machinery in modern manufacturing process requires effective on-line monitoring and fault prediction.

Machinery monitoring options are rarely mentioned in case of new machinery. In case of modern manufacturing equipment, a monitoring system is assumed to be part of the machinery. However, in many cases the manufacturing equipment can be destroyed either because of a wrong mode of operation or trivial part failures without any advance indication of potential problems from the on-board monitoring system. The main reason for this is the fact that a complex monitoring system increases the cost of the machine, which is a competitive disadvantage in the low budget metal working machinery market.

Machinery that is 30–40 years old is typically quite massive, which assures stable machining and suppresses vibrations. These properties make such machines valuable and they are still running at shop floors for tens of years. The main disadvantage of such machines lies in the fact that they are not equipped with a monitoring system or the functionality of the latter is too limited.

The above-mentioned cases require installation of a modern wireless monitoring system to maintain the advantages of the existing machinery and ensure safe operation on the manufacturing floor. Installing a monitoring system, based on wireless sensor nodes, is relatively cheap and it can be fitted to both old and modern manufacturing equipment.

Attaching embedded computers with a wireless communication interface, which form a wireless sensor network (WSN), onto machinery for monitoring machinery condition keeps the price of the solution reasonable, but provides extra safety to the existing process. The installation cost of cables in an industrial plant can vary greatly based on the type of plant and physical configurations. Studies have shown that average cable installation cost is between 10 and 100 $ per foot [1], but in a nuclear plant even 2000 $ per foot.

Research in the field of smart dust was started as a research project in 1997 by University of California computer science professor Kris Pister. A smart dust mote is a tiny computer equipped with a processor, some memory, a wireless communication interface, an autonomous power supply and a set of sensors appropriate for the task at hand. In order to prolong the battery life, the motes are activated only when communicating or processing the data. When the smart dust concept was introduced (this is true also currently to a certain extent) it was very advanced compared to existing solutions as it potentially enabled to build networked intelligence into everything from walls to laptop computers. In the last decade many studies have been performed to transform the dream into reality. Examples can be brought from machinery monitoring research community where the technology has been applied in condition monitoring in end-milling [2] and in drilling machines [3]. Controlling of a programmable machining system has proved to be an exceptionally difficult problem due to the protocol and interfacing [4].

In condition monitoring applications, a parameter (or several parameters) that reflect the state (condition) of the machinery is (are) monitored. Before a condition monitoring application can be deployed, models are developed that reflect the correlation between the state of the machine and the monitored parameter. Several parameters can be combined in order to obtain clearly understandable results. From the value of the parameters the state of the machine is then estimated at runtime, enabling the detection of failures and critical modes of operation. Condition monitoring is one of the major components of predictive maintenance. The use of condition monitoring allows maintenance to be scheduled, or other actions to be taken to avoid the consequences of failure, before the failure occurs. Nevertheless, a deviation from a reference value (e.g. temperature or vibration behaviour) must occur to identify upcoming damages. Predictive maintenance does not predict failure. It only helps to predict the time of failure. The failure has already started and the sensor system can only measure the deterioration of the condition. Early planned pauses in manufacturing for changing some parts are more cost effective than allowing the machinery to fail.

However, the WSN based monitoring solutions pose some restrictions to the monitoring approach. As the communication bandwidth is quite limited (when compared to conventional wired networks), the objective is to process the data acquired via sensors locally to the highest level of abstraction possible and to communicate only a limited amount of data. The issue of limited bandwidth is elevated by the fact that potentially the number of sensing points is high, so only high-level information should be communicated via the network [5]. In addition, the WSN nodes are typically battery powered and with limited computational capacity, which means that the algorithms employed in the nodes should have low requirements for the computational power. This study provides source information for the evaluation of data processing algorithms and methods that can be employed in the manufacturing equipment monitoring.

In the monitoring process, the cutting force ratio is used to predict the in-process surface roughness regardless of the cutting conditions. Using regression analysis, regression coefficients are calculated and used in the surface roughness prediction model for the turning machine. This exponential function represents the relation between surface roughness, the cutting force ratio and other cutting parameters [6].

The aim of the paper is to present first steps in the concept of measuring and identifying operation modes of machinery for detecting unwanted machining status and preventing tool braking.

Prototype measuring devices were designed and assembled and experiments were conducted in a controlled environment. Measured parameters were acceleration for detection of the vibration and acoustic signals. Experiments were conducted on a turning machine.

2. ACCELERATION MEASUREMENTS

2.1. Measurement method

Vibration of the unit was measured with a solid-state micro electromechanical system (MEMS) accelerometer LIS3LV02DQ. This device is capable of measuring acceleration in three directions in the range of ±2g at 12 bit resolution. Gravity of Earth was eliminated from measurement results. This sensor type was selected as it has a suitable measurement range and accuracy, small footprint ($7 \times 7 \times 2$ mm), internal digital conversion unit with built-in noise filtering, suitable electrical interface and is readily available in prototyping form. The same sensor can be used in the final and optimized WSN as it has suitable electrical interface (SPI) and very low power requirements (0.8mA@3.3V). The sensor was interfaced to a computer during the experiments via the low-voltage SPI bus. An additional data acquisition/interface board was installed between the sensor and the main data acquisition computer as the computer was not equipped with the SPI interface. The data acquisition board was a WSN node prototype, based on the Atmel AVR XMEGA microcontroller. As the data acquisition board is essentially a fully fledged WSN node, it is also capable of reading sensor data, buffering it and later forwarding it to the computer in serial (RS232) format. Considering the constraints of the interface board memory, processing power and serial communication acquisition speed, the sampling frequency 640 samples/s was chosen. It may be desirable to use a higher sampling frequency, but in order to acquire data for all the axes some tradeoffs had to be made. Since the frequency of the vibrations, generated in the monitored equipment, were not known, the sampling frequency used served as a starting point to evaluate the possible monitoring solutions applicable for the given device. The measuring period for each sampling session was 30 s. The resulting data sets consist of 19 200 samples for each axis.

In the final and optimized WSN the serial (RS232) data link will be replaced with a wireless communication module that is already present on the prototype board. Depending on the analysis results and firmware, it is possible to transmit live measurement information continuously or only just the identified state of the machinery being monitored.

2.2. Measurement process

All measurements were made on a CNC turning machine 16A20F3RM132. The acceleration sensor was bolted to the CNC turning lathe carriage and 5 sets of data acquisition experiments were conducted. Accelometer also measures gravity of Earth and its influence is unequal in all 3 axes. For better clarity and comparability of results, gravity of Earth was eliminated from acceleration measurement results before data processing.

Tests 1 and 2 were made just with an empty spindle at speed 2400 min^{-1}. Test 3 was made at spindle speed 600 min^{-1}, feed rate 0.3 mm/s with real turning. Test 4 was made at spindle speed 2400 min^{-1}, feed rate 0.3 mm/s with real turning. Test 5 was made at spindle speed 600 min^{-1}, feed rate 0.3 mm/s with real turning. Tests 4 and 5 also include an event of failure. The result of failures in tests 4 and 5 was tool breakage. Test parameters are shown in Table 1.

2.3. Analysis of the results

Results were analysed in the time domain. Mean values of the acceleration series are stable and this means that sensor was fixed reliably during the whole measuring process.

Standard ranges of the acquired data series that are presented in Table 2 show extreme values in test 4, but also high value in test 5. Both of these tests include tool breakage. The results of the other tests are quite similar to each other. Distinction between different modes of the turning lathe can be observed better in graphical representation of the acceleration values presented in Figs. 1–5, corresponding to tests 1–5. Every figure contains measurements of acceleration in three directions, presented in same scale.

First tests were made only with the turning spindle, without cutting process. The reason was to get 0-level background for the tests 3–5. Tests 1 and 2 that were conducted with exactly the same turning parameters show that their value difference is negligible (max 7% in z axis). It shows that test results are repeatable and test values are reliable.

Comparison of tests 3 and 5 illustrates the difference between normal operation and failure during operation. Tests 3 and 5 were made with the same operational parameters. The only difference was the failure of the tool. The y axis value was 24% higher in fault situation than in normal operation mode. This distinction allows fault identification.

Table 1. Acceleration test parameters

Test No.	Spindle speed, min^{-1}	Feed, mm/rev	Turning	Failure	Linear velocity, m/min
1	2400	0			
2	2400	0			
3	600	0.3	x		180
4	2400	0.3	x	x	723
5	600	0.3	x	x	180

Table 2. Acceleration range values along different axis during the measuring period

Test No.	x	y	z
1	116	160	88
2	119	156	94
3	125	161	89
4	185	234	385
5	133	200	94

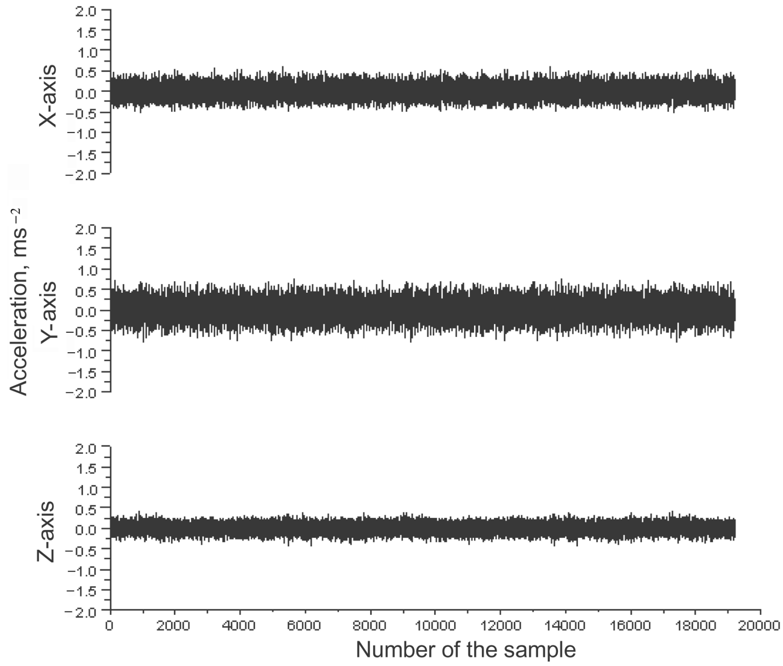

Fig. 1. Noise floor level test No. 1.

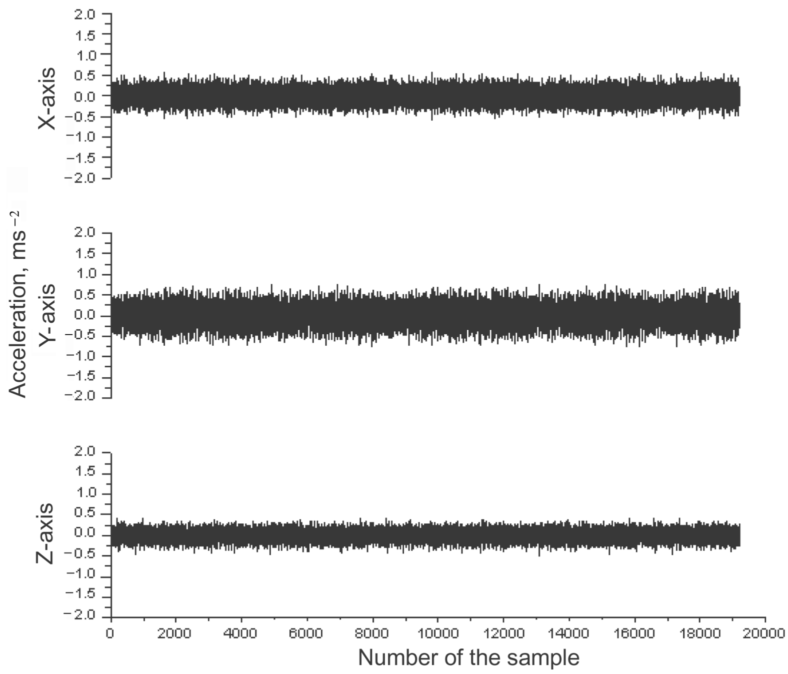

Fig. 2. Noise floor level test No. 2.

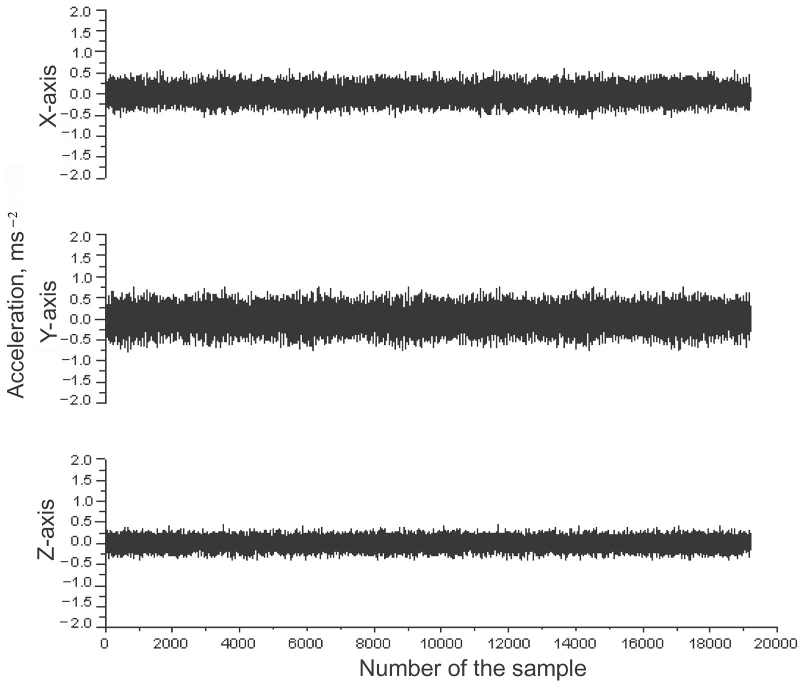

Fig. 3. Normal working mode test.

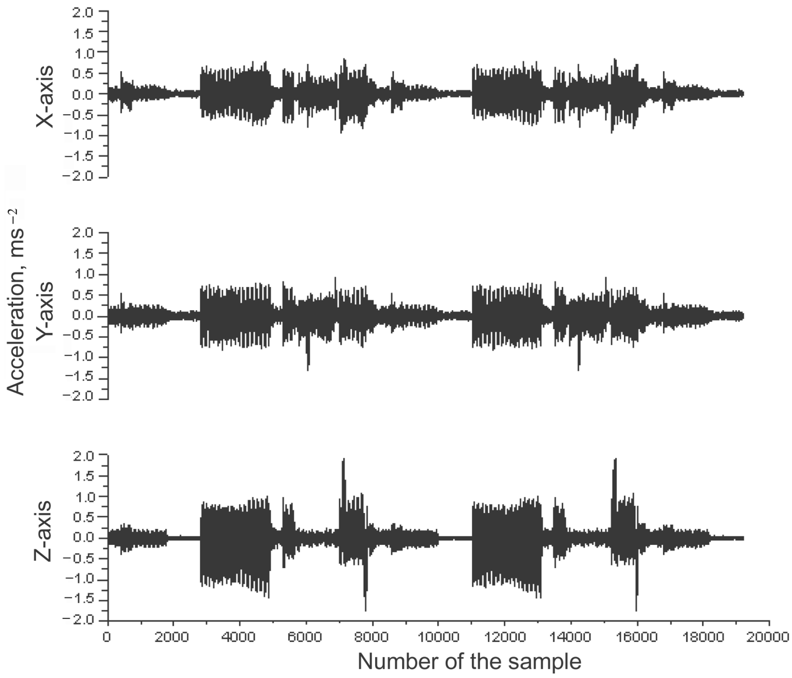

Fig. 4. Fault situation test in high speed.

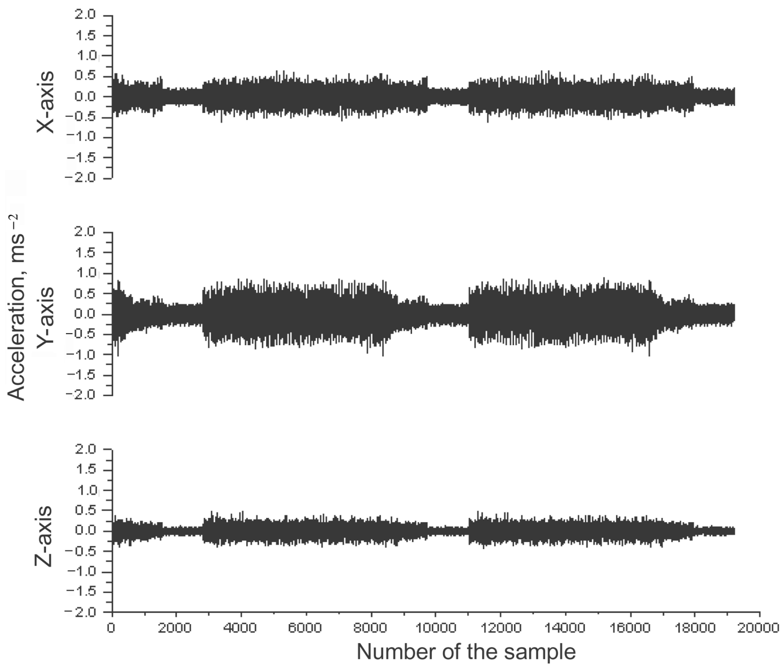

Fig. 5. Fault situation test in normal speed.

Tests 4 and 5 illustrate rapidly growing vibration in breaking situation at higher spindle speeds. With higher spindle speeds the failure pattern is more distinct.

2.4. Conclusions from the measurement results

It is possible to identify different modes of operation and predict fault situations by measuring acceleration of the turning lathe carriage. The identification task is simpler at higher spindle speeds as the pattern is more distinct in that case. Important is to detect changes in early stage to take the action for avoiding faults. For getting more reliable and more specific feedback, a group of sensors is to be used.

Instead of or in addition to the accelerometer, also piezoelectric sensors could be used for detecting vibration values. Piezoelectric sensors can measure with higher frequency, but only in one direction. Measuring with higher frequency can bring out more distinct information and help in analysing section.

Deeper data analysis is needed to find informative patterns to detect machining variations in early stages to avoid faults and unplanned pauses in manufacturing. Regression analysis and artificial neural networks are options in creating operative sensor network feedback model.

3. ACOUSTIC MEASUREMENTS

3.1. Measurement method and description

Acoustic signal of the unit was measured with SM58 microphone and the analogue signal was converted to digital using Roland Edirol UA-25EX audio signal processor. The digitized signal was recorded in a PC. All measurements were made on the CNC turning lathe 16A20F3RM132. The microphone was positioned near the cutting area. The acoustic signal was sampled at a sampling rate of 22 050 Hz and recorded to a *wav* file in the PC. Data was sampled during a turning work cycle (starting up the engine, turning, turning fault and turning off the engine).

3.2. Measurement results

Operation mode classification was made by applying spectral analysis to the sampled signal. Fourier transforms were performed on sections of recorded samples acquired during different modes of operation and the resulting frequency spectrums were compared with each other.

Figure 6 represents the spectrums of signals acquired in different modes of operation. In mode 1 the feed engine works only, in mode 2 the spindle engine is turned on, in mode 3 the lathe is in normal operational mode and in mode 4 a fault occurs.

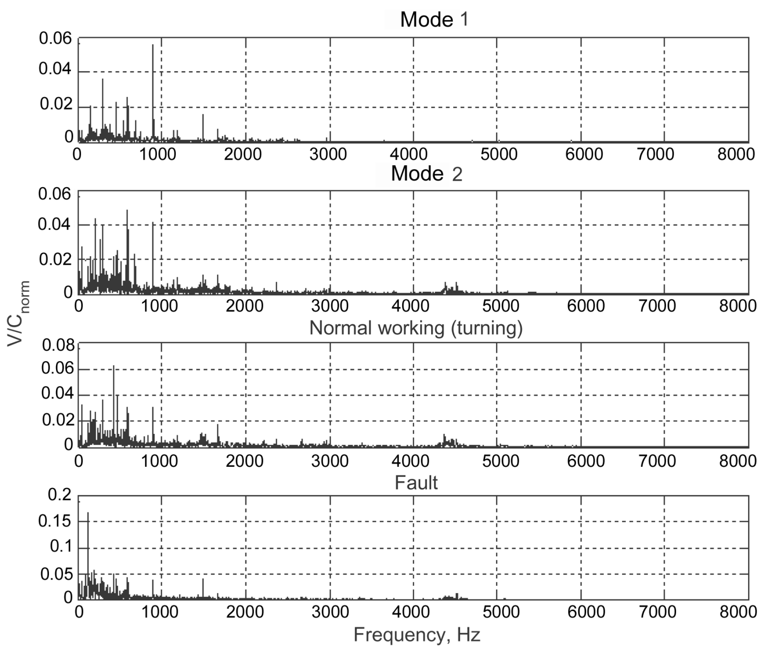

Fig. 6. Modes 1–4 in turning.

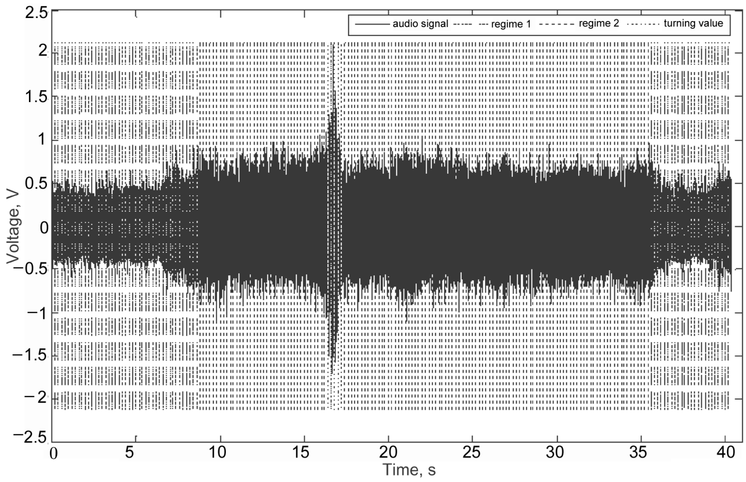

Fig. 7. Acoustic signals in different modes.

The spectrums of signals acquired in modes 2 and 3 are similar and distinguishing them from each other is difficult. For that reason the spectrum for mode 3 is discarded and only the spectrums of signals acquired in modes 1, 2 and 4 are analysed. In Fig. 7, acoustic signals are measured with 0.2 s interval. The whole length of the test was 40 s. Figure 7 shows a different pattern of the signal in the feed engine working mode, turning mode and in the occurrence of a fault.

3.3. Conclusion of the measurement result analysis

Acoustic measurements identified 3 different recognizable operating modes. In this case acoustic and acceleration measurements were made separately. But combining and comparing these with each other can give more precise information for creating the model.

Various acoustic signals, common in shop floor and other machineries, can cause extra noise and influence measured acoustic signal. For this reason, using piezoelectrics sensors can give more reliable information. When acoustic sensor measures air vibrations then piezoelectric sensor measures practically the same vibration from the solid part surface, without air involvement.

4. MONITORING WITH SMART DUST

The tests described in the paper were performed using wired sensors. For real applications in the manufacturing floor it is essential to employ wireless sensors that are integrated to an e-manufacturing system [7]. As suggested in the introduction, wireless sensors or smart dust motes can be used in such monitoring applications in addition to the wide range of other smart dust potential applications [8]. Smart dust motes can be equipped with a wide range of sensors, so depending on the application the properties of a smart dust mote can vary substantially as the processing unit of the mote may be also different, to be able to process the data collected by the sensors.

For monitoring various types of machinery (and different properties of specific manufacturing equipment), different sensors must be used and the motes must be assembled correspondingly from modules. Different smart dust motes can be equipped with different sensors and the processed measurement results can be exchanged between the motes and fused in the field by the motes themselves. This allows the generation of data with high reliability directly in the field, reducing potentially the bandwidth requirements of the system and making it possible to increase the number of sensing points by installing a greater number of sensors and motes on the equipment.

So far the manufacturing reports are generally created through manual triggering by the user. However, especially for standard reports, it makes sense to have the option to use automatic, timed report creation. The proactive distribution of important information through the manufacturing execution system is especially useful in connection with mobile end devices [9]. We could include motes in this report chain, as proved in this research.

Biggest challenge for smart dust is to achieve noiseless data transmission in the manufacturing environment. Electromagnetic interferences can be decreased to a minimum by increasing the number of motes and placing them closer.

5. FURTHER RESEARCH

The test results presented in this paper are just a little touch of machinery monitoring. Further research is required to develop and implement practical solutions.

1. Comparison of different type of sensors, measuring values and their analysis results from the perspective of pattern intensity.
2. The optimal sensor placement must be determined for every type of machine in order to acquire the parameters of interest.
3. Manufacturing equipment must be categorized from the monitoring perspective to develop and employ fixed configurations of monitoring equipment on different machines.
4. In order to determine the tool wearing pattern, experiments must be conducted also with different tool wear levels.

6. CONCLUSIONS

Experiments showed that different modes of operation of the manufacturing equipment can be determined using basic sensors and signal processing methods.

Measurements made with the accelerometer show the vibration range that allows distinguishing fault situation from normal operation. Acoustic measurements permit to distinguish idle operation, normal operation and fault situation.

In order to implement an automated monitoring system for manufacturing equipment, the patterns for different modes of operation must be determined initially, after which the WSN technology can be used to detect the modes of interest.

ACKNOWLEDGEMENTS

This research was supported partly by the competence centre IMECC, Estonian Ministry of Education, Research Project SF0140113Bs08, and Estonian Science Foundation (grant F7852).

REFERENCES

1. Tiwaria, A. and Lewis, F. L. Wireless sensor network for machine condition based maintenance. In *Proc. 8th International Conference on Control, Automation, Robotics and Vision*. Kunming, 2004, 461–467.
2. Wright, P., Dornfeld, D. and Ota, N. Condition monitoring in end-milling using wireless sensor networks (WSNs). *Trans. NAMRI/SME*, 2008, **36**, 177–183.
3. Shin, B., Kim, G., Choi, J., Jeon, B., Lee, H., Cho, M., Han, J. and Park, D. A web-based machining process monitoring system for E-manufacturing implementation. *J. Zhejiang Univ., SCIENCE A*, 2006, **7**, 1467–1473.
4. Xu, X. *Integrating Advanced Computer-Aided Design, Manufacturing, and Numerical Control: Principles and Implementation*. Information Science Reference, New York, 2009.
5. Zhao, F. and Guibas, L. *Wireless Sensor Networks: An Information Processing Approach*. Morgan Kaufmann Series in Networking, San Francisco, Ca, 2004.
6. Tangjitsitcharoen, S. and Senjuntichal, A. Monitoring of surface roughness in CNC turning process. In *Annals of DAAAM 2010 & Proc*. (Katalinic, B., ed.). DAAAM International Vienna, Vienna, 2010, 1391–1392.
7. Koç, M., Ni, J., Lee, J. and Bandyopadhyay, P. Introduction to e-manufacturing. *Int. J. Agile Manufact.*, 2003, **6**, 97-1–97-9.
8. Haenggi, M. Opportunities and challenges in wireless sensor networks. In *Smart Dust: Sensor Network Applications, Architecture and Design* (Mahgoub, I. and Ilyas, M., eds). Taylor & Francis, Boca Raton, 2006, 1-1–1-14.
9. Meyer, H., Fuchs, F. and Thiel, K. *Manufacturing Execution Systems: Optimal Design, Planning, and Deployment*. McGraw Hill, New York, 2009.

Arupuru rakendused tootmisprotsesside seirel

Tanel Aruväli, Risto Serg, Jürgo Preden ja Tauno Otto

Üks potentsiaalne arupuru kasutusvõimalus tööstuses on tsehhis huvipakkuvate protsesside seiramine ja eriolukordade avastamine. Kübemed koguvad ja töötlevad andmeid, edastades valitud info kas keskse andmebaasi või otse

tootmisjuhi käsiseadmesse. Käesolevas artiklis on käsitletud arvjuhtimisega tööpingi vibratsioonide ja müra mõõtmist, kuid arupuru võib kasutada ka temperatuuri ning teiste oluliste parameetrite mõõtmiseks. Esitatud lahendus võimaldab tuvastada tsehhis muutusi tehnoloogiaseadmete tööprotsessis ja prognoosida võimalike probleemide teket, vältides nii tootmises planeerimata remondipause.