THESIS ON MECHANICAL ENGINEERING E89

Wireless Real-time Monitoring of Machining Processes

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TUT PRESS

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Dissertation was accepted for the defence of the degree of Doctor of Philosophy in Engineering on November 26, 2014.

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Defence of the thesis: January 14, 2015

Declaration:
Hereby I declare that this doctoral thesis, my original investigation and achievement, submitted for the doctoral degree at Tallinn University of Technology has not been submitted for doctoral or equivalent academic degree.

Tanel Aruväli ....

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ISSN 1406-4758
ISBN 978-9949-23-721-0 (publication)
ISBN 978-9949-23-722-7 (PDF)

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CONTENTS

LIST OF PUBLICATIONS

The doctoral thesis is based on the following publications that are referred to in the text as follows [Paper I – Paper IV].

Paper I	Aruväli, T.; Serg, R.; Preden, J.; Otto T. (2011). In-process determining of the working mode in CNC turning. *Estonian Journal of Engineering*, 17(1), 4–16.
Paper II	Aruväli, T.; Reinson, T.; Serg, R. (2011). Real-time machinery monitoring applications in shop floor. *Proceedings of the World Congress on Engineering and Computer Science*, 1, 337–342.
Paper III	Aruväli, T.; Serg, R.; Otto T. (2012). Machinery utilization monitoring and pause identification prototype model design. *Proceedings of the 8th International Conference on DAAAM Baltic Industrial Engineering*, 256–261.
Paper IV	Aruväli, T.; Maass, W.; Otto T. (2014). Digital object memory based monitoring solutions in manufacturing processes. *Procedia Engineering*, 69, 449–458.

The copies of the publications are included in Appendices.

INTRODUCTION

The main component for success for manufacturing enterprises is efficiency in work flow that creates the bases for high productivity. Machinery's high-level power and speed capabilities are only some indicators of workstation productivity. Another and even more important indicator is human activity and knowledge in arranging, planning and running a workstation. The key words of modern manufacturing system are small batches, flexibility, shortened production cycles, reduced work-in-progress, make-to-order, and almost instantaneous delivery [Viswanadham *et al*., 1997]. Fast and informative feedback is needed from shop floor to fulfil modern manufacturing system requirements. The need for a technology-based real-time wireless sensor network (WSN) monitoring system, employed by embedded computers, is getting more critical than ever before. This is the element that enables every interested party in a manufacturing enterprise to get vital information to make knowledge-based decisions according to real-time situations, which are cognitively hard to comprehend. Furthermore, monitoring increases sustainability by reducing waste. It is vitally important to make the monitoring system affordable also for small and medium enterprises (SMEs) that are main innovators and job creators. On the other hand, WSN without knowledge-based management can be disturbing and even increase idle time. Therefore, explicit models and techniques for comprehensive monitoring network are crucial to obtain expected utility.

Changes in manufacturing methods, energy sources, machine tools, cutting tools, decision making processes, management tools, product development methods, products and customer position are just some and most visible changes over the time. Globalising competition between manufacturers, new technology sectors, advanced materials and increasing workforce cost have been main drivers behind these changes. In the last decade, developed countries have lost a lot of production work to developing countries with emerging economies, such as China, India, and Bangladesh. Manufacturing in developed countries has moved from mass production to mass customisation. Wide product ranges with frequent machine tool adjustments have historically been more workforce capacious. However, these days there is an opposite tendency to automate feedback and communication in the management of small batches and as a result to derive more profit. This is achieved by bringing more intelligent solutions to the manufacturing environment to promote the manufacturing of small batches with less cost.

It is said that information and communication technology (ICT) is the foundation of innovation in all other economic sectors and ICT additionally functions as a growth accelerator for all key branches [Wahlster, 2007]. In the last decade, ICT development has been so fast that applications in production environment have not get the full integration with state of the art technology. It means that we basically have the technology but applications have not kept up with latest technological developments. It shows high potential of real-time communication and monitoring applications in the shop floor.

According to European Commission's statistics, industrial production gives 16% of Europe's gross domestic product (GDP) and it continues being the key driver for innovation and job creation. In the EU, 31 million persons were working in the manufacturing sector in 2009. It is known that every position in the manufacturing sector creates a related position in the service sector. [European Commission, 2013]

Main objectives and activities of research

<u>The main objective</u> of research is to study and develop monitoring of machining processes, focussing on SMEs. The specific aims are to develop methodology to analyse machine tools status in real time, elaborate a demonstrator toolkit for testing the methodology, and find novel tools for automatic real-time monitoring in machining.

<u>The main activities</u> of research are the development of planning and structuring of monitoring system; digital object memory (DOMe) integration into the automated quality control; suitable measuring and analysis methods evaluation and comparison; development, design and construction of a status monitoring and pause reasoning demonstration toolkit.

Scope and limitations of research

The main objects of research are machining processes monitoring applications in industrial SMEs. Main attention is on monitoring modules, such as machine tool status monitoring with pause reasoning, cutting process working mode detection, tool insert condition monitoring and part quality monitoring with on-board data storage. So far, the most researched module – machine tool health monitoring (condition monitoring) – is observed as a part of the monitoring system. Therefore, it is out of the scope of a deeper investigation. Most experiments are carried out mainly based on lathes, but can be expanded also for other machine tools.

Focus is on the wireless real-time data collection and distribution, where reasonable. Many of the experiments are implemented using wired solutions and posterior analysis. However, components in experiments are chosen according to further maximal usage in wireless solutions.

Machine tool reconstruction for the monitoring purposes is out of the scope. Therefore, machine tool adaptive feedback is not researched. Instead, focus is on machine tool's supportive components and infrastructure, such as smart cutting tools, intelligent manufacturing environment and increasing the situation awareness of operators and other related parties.

Research focus is on monitoring modules of machining processes. Therefore, manual work station monitoring with workman performance tracking is not covered. Also logistics monitoring is beyond the scope.

The concept of DOMe-based machining process monitoring is studied theoretically and does not include experiments.

Main hypothesis of research

- Machining in-process vibrations and acoustic signals enable to evaluate machine tool status and working mode.
- Wireless machining processes monitoring system can be built modularly and is easily adaptable to collect in-process data in real time. Monitoring modules can be added one by one (the monitoring system is expandable).
- Monitoring modules can be adapted on existing machine tools. Additional changes by machine tool manufacturers are not needed.

Novelty

The following novel solutions are proposed and presented in the thesis.

- A new approach to planning and structuring for the monitoring of machining processes.
- New sensing, feature extraction and analysis combinations for various machine tools status detection in the shop floor.
- A novel WSN-based status monitoring and pause reasoning demonstration toolkit with real-time graphical user interface (GUI).
- The concept of DOMe integration into part and machining quality automatic real-time monitoring in turning.

Contribution of the thesis and dissemination

This research can be recommended for reading especially for production managers who wish to optimise machining processes through automatic real-time informative feedback in industrial SMEs. It is also valuable for everybody who is interested of state-of-the-art industrial monitoring methodologies. Current research first introduces the field of industrial monitoring and its modules. It analyses and explains the features, architecture and sample solutions of knowledge-based monitoring application implementation in SMEs. This research is one milestone in industrial monitoring system development and is open for further investigation and development in line with technological evolution.

The results of the thesis are internationally introduced. They were presented in 12 different peer-reviewed international conferences on three different continents. The author has published 15 international scientific papers directly associated with the research, of 11 of which as the first author. The papers are indexed in databases as ISI Web of Science, Scopus, and ScienceDirect.

LIST OF ABBREVIATIONS AND SYMBOLS

Abbreviations

A/D	Analogue-to-Digital
ANN	Artificial Neural Network
CAD	Computer-Aided Design
CAM	Computer-Aided Manufacturing
CEO	Chief Executive Officer
CNC	Computer Numerical Control
CPPS	Cyber Physical Production System
DAQ	Data Acquisition
DOMe	Digital Object Memory
FFT	Fast Fourier Transform
FoF	Factories of the Future
FoW	Field of View
G-code	Code in G Programming Language
GDP	Gross Domestic Product
GUI	Graphical User Interface
IC	Integrated Circuit
ICT	Information and Communication Technology
ID	Identification
IoT	Internet of Things
IP	Internet Protocol
IT	Information Technology
MFCC	Mel-Frequency Cepstral Coefficients
NI	National Instruments
OEE	Overall Equipment Effectiveness
OMM	Object Memory Model
OWL	Web Ontology Language
PC	Personal Computer
PMMA	Polymethyl Methacrylate
PnP	Plug-and-Play
PPP	Public Private Partnership
RF	Radio Frequency
RFID	Radio Frequency Identification
RMS	Root Mean Square
SemProM	Semantic Product Memory
SME	Small and Medium Enterprise
SMLC	Smart Manufacturing Leadership Coalition
SRP	Steered Response Power
TEEP	Total Effective Equipment Performance
UI	User Interface
URL	Uniform Resource Locator
W3C	World Wide Web Consortium
WAV	Waveform Audio File

WSN	Wireless Sensor Network
XML	Extensible Markup Language

Symbols

A	machine tool availability
C	a constant which depends on workpiece material and cutting tool
C_c	a constant which depends on in-process signal features
C_1	a constant which depends mainly on the size of cut, workpiece material and cutting tool
d	depth of cut
f	frequency
f_c	feed rate
$Mel(f)$	Mel-frequency scale
P	machine tool performance efficiency
Q	products quality rate
R	range
R_{max}	maximum range value
R_{min}	minimum range value
R_R	range of range values
Rz_t	theoretical ten-point mean roughness
Rz_s	in-process signal based estimated ten-point mean roughness,
r_E	tool insert nose radius
S_f	in-process signal feature
T	actual cutting time required to dull tool
v	cutting speed
$x; y$	exponents which vary with workpiece material and cutting tool
x_{min}	minimum value in selection
x_{max}	maximum value in selection
$\bar{x}_R$	arithmetical mean of range values
η	exponent that varies with workpiece material and cutting tool

1 LITERATURE REVIEW

Together with overall industrial applications development, also monitoring of machining processes have been in continuous development. Different physical parameters have been detected and analysed using various methods to study in-process signals and to transfer it into understandable shape. WSN and radio frequency identification (RFID) are used as technological bases for wireless data transmission and identification. DOMe is one of the RFID based solution that enables to personalise and enrich every single part with manufacturing related information.

1.1 Background

Continuous development of manufacturing systems and their technological bases have driven us close to the next industrial revolution (Figure 1.1). The first industrial revolution took place at the end of the 18th century when steam and water were taken into usage as energy carriers in mechanical production facilities. The second industrial revolution started through the introduction of mass production and the spread of electricity as energy carrier. The third revolution, which is also called digitalisation, brought further automation of manufacturing through the introduction of electronics and information technology (IT) solutions. Many of researchers find that we are close to the fourth industrial revolution that bases on cyber physical production system (CPPS) [Wahlster, 2013; Schlick, 2012].

Figure 1.1 Industrial revolutions

According to an ASQ outlook survey in manufacturing enterprises [ASQ, 2013], 29% of managers who are interested in using smart manufacturing systems, but do not implement them, say that cost is the main challenge. 79% of managers who use a smart manufacturing system answered to the question "What were the challenges of implementing smart manufacturing technologies at your organisation?" that cost was the biggest challenge to implement the system. At the same time, smart manufacturing system users are satisfied. Main benefits have been achieved in increased efficiency (82%) and increased product quality (56%). This survey shows how hard it is to implement a smart manufacturing system. At the same time it shows how much benefit implementation can give.

1.2 Monitoring applications in machining

Machining processes have been the object of research for many decades. Changes in machine tool components, their performance quality and tool life have been investigated using different physical parameters. Vibration [You *et al.,* 2011], acoustics [Ren *et al.,* 2014], cutting force [Denkena *et al.,* 2014], and temperature [Creighton *et al.,* 2010] have been the main in-process sensing parameters to evaluate the condition of machining processes. Also visual in-process detection has been used with a CCD camera [Otto *et al.,* 2003]. For electrical motors, monitoring current [Philipp, *et al.,* 2012] and voltage [Ottewill *et al.,* 2013] have been used. In some cases sensor fusion is applied [Loutas *et al.,* 2011].

The most used metal working machining processes, such as turning [Saravanan *et al.,* 2006], drilling [Eckstein *et al.,* 2012], and milling [Wright *et al.,* 2008] have been mainly researched. In addition, laser cutting [Yilbas, 1996], welding [Liu *et al.,* 2014], water jet cutting [Goletti *et al.,* 2013], wire electro-discharge machining [Cabanes *et al.,* 2008], etc., processes have been covered. Also different types of production lines [Amos *et al.,* 2008; Mokhtar *et al.,* 2011] have been monitored. In principle, there is an unlimited number of machine tools and their processes that can be in-process sensed and evaluated for knowledge-based decision making.

Condition monitoring helps prevent damage to components and predicts their degradation. The main components of rotating machine tools to cover with predictive maintenance have been engines [Philipp, *et al.,* 2012], spindle bearings [Glavatskih, 2004], and gear-boxes [Ottewill *et al.,* 2013].

Machine tool working condition, cutting tool wear and part surface roughness are strongly related. They have been studied using different type of in-process signals and various analysis techniques combined with cutting input parameters. Vibrations, acoustics and cutting forces as in-process output parameters were evaluated in time domain according to maximum value, standard deviation, root mean square (RMS), and mean value [Aliustaoglu *et al.,* 2009]. Condition-based tool wear has been analysed using in-process vibrations, acoustics and cutting forces together with wavelet analysis [Li *et al.,* 2007]. In-process prediction of surface roughness model has been developed in ball-end milling [Tangjitsitcharoen *et al.,* 2010a] and computer numerical control (CNC) turning [Tangjitsitcharoen *et al.,* 2010b]. Both of the models use inputs for regression analysis as in-process cutting forces and cutting input parameters. An artificial neural network (ANN) model has been developed to estimate in-process surface roughness and tool wear level [Ali, *et al.,* 2010]. Models show reliable results but implementation in real time is problematic due to lack of automated information about cutting input parameters.

For the analysis of results, mostly time domain and frequency domain solutions have been used. Linear correlation has been found between surface roughness and vibrations in end-milling [Wright *et al.,* 2008].

During the last decade different research topics have focussed on wireless real-time monitoring in the shop floor. They all have a slightly different core idea but one of their main bases has been machine tool real-time monitoring and information distribution.

K. Pister started the research and development of the so-called *Smart Dust* [Kahn *et al.,* 1999] in 1997. A smart dust is a small wireless sensor node with processor, memory, wireless communication interface, and autonomous power supply. The aim was to reduce the size of the node to one cubic millimetre volume but a working entity with this size is still not realised.

In the beginning of the 2000s, the concept of e-manufacturing [Koç *et al.,* 2005] was with high importance. The part related to e-manufacturing monitoring was called e-maintenance. Tools such as signal processing, feature extraction, performance assessment, performance prediction, performance diagnoses and right information distribution to right people in real time are considered in an e-manufacturing intelligent maintenance system [Lee *et al.,* 2006].

Different machine tool monitoring systems have been proposed. A LabView-based smart machine supervisory system [Atluru *et al.,* 2012] has been designed and implemented. It integrates and coordinates monitoring modules as cutting tool condition monitoring, on-machine probing, intelligent process planning, machine tool metrology, and machine tool health and maintenance. A PXI hardware and LabView software-based online broaching process monitoring system [Shi *et al.,* 2006] has been developed. A smart sensor platform [Ramamurthy *et al.,* 2007] has been developed to support communication and plug-and-play (PnP) capability. It includes specially designed smart sensor nodes, application integration software, and real-time control to achieve predictive maintenance of machine tools.

Today, the vision of intelligent monitoring system in the factory of the future is based on CPPS [Zühlke *et al*., 2011]. The main idea of the CPPS is that physical manufacturing flow and digital information flow are parallel fully integrated inseparable phenomena. The core aim is that instead of operators, a product controls the machining processes through semantic context-based communication. Ontology languages such as web ontology language (OWL) are pioneers in semantic knowledge representation in manufacturing.

1.3 Importance and application areas of wireless sensor network and radio frequency identification

WSN and RFID technologies have been widely used in monitoring and tracking applications in various areas. Furthermore, for efficient value stream mapping in the shop floor, WSN and RFID integration is suggested to be performed [Ahmed *et al*., 2014].

High potential areas of WSN monitoring are medical care, home intelligence, military applications, environment monitoring, surveillance, scientific exploration, factory instrumentation monitoring, traffic and smart road monitoring [Wang *et al.,* 2006]. In the manufacturing industry, wireless sensors are mostly used for machine tool components condition monitoring to provide preventive maintenance and diagnostics, but also application for part tracking [Seitz *et al*., 2010] has been proposed.

RFID is mostly used for identification, tracking, and tracing of items. For manufacturing control, RFID-based applications can be used in part procuring, manufacturing scheduling, inspection, warehousing, dispatching, and in maintenance [Brintrup *et al*., 2009]. It is also a tool for real-time coordination of material flows and manufacturing tools [Aruväli *et al*., 2012]. So far the most utility has been gained in logistics.

Various manufacturing process monitoring applications have been used in the spreading of industrial manufacturing. Already many decades ago solutions such as andon lights, tracking sheets, reject, goal and variance counters were used that have outdated technical solutions today but their core idea has moved to the state-of-the-art monitoring solutions. Already 50 years ago, sensors were used on machine tools for the monitoring [Foster, 1967] purpose. In nowadays solutions, sensors equipped with processors and adaptive algorithms are capable of communicating with each other, with machines, and with environment. They perform analysis, study, take decisions, and activate actuators. At present, the keywords of high-level shop floor monitoring are real-time feedback, wireless connections and Internet of things (IoT).

1.4 Concept of digital object memory

According to the CPPS, every workpiece is equipped with a DOMe [Haupert, 2012] that carries information about its manufacturing processes. In this way, every particular workpiece orders its machining processes based on the information in its related memory. Intelligent workpieces and intelligent machines can communicate with each other, optimise manufacturing processes, and control quality. Additionally, machining process monitoring information can be automatically saved to the DOMe after every operation to track its quality parameters all over the product life cycle. Hence, the DOMe can be used through a product life cycle [Schneider *et al*., 2008]. Only particles of this concept are implemented in corporate enterprises. This concept is developed mostly in manufacturer-independent research and a demonstration plant *SmartFactory* [SmartFactory, 2014].

The DOMe is a state-of-the-art technology tool that has great potential in machining process quality and part quality monitoring. Furthermore, it expands part and product related communication and enables real-time feedback. The DOMe usage is one component of utilising the CPPS in shop floor. The three pillars of the CPPS are smart machine tools, smart products, and an augmented operator. The DOMe focusses on a smart product with broad communication opportunities with related objects. The DOMe paves the way for the concept of IoT in the shop floor.

According to the CPPS, products are the most important things in the shop floor and every process performed is carried to service the products. The DOMe helps identify every particular workpiece, part, assembly, and product. It makes every one of them unique by adding object-related information storage space with communication supportive elements to every object. Instead of managing machining processes from an office, the DOMe gives more flexibility by utilising workpieces, such as machining processes managers. The idea is that when a workpiece enters the shop floor, it already knows which processes it has to follow and how to get manufactured. It means that a workpiece carries input information about its manufacturing processes, such as codes in the G programming language (G-code) and controller input codes. Workpieces are processed according to this data throughout the manufacturing processes. In principle, a workpiece becomes the centre of manufacturing and organises it by interactive communication.

The DOMe usage gives the most utility when it is integrated already in the phase of workpiece or raw material and is used all over the product life cycle [Schneider *et al*., 2008]. It covers manufacturing, transportation, retailing [Maass *et al*., 2008; Haupert, 2011a], service, and recalls. So far, mainly the transportation cycle is investigated.

Assembling parts to an assembly collects many DOMes into one object. For eliminating related disorders, a schema is developed for integrating particular object-related information into one. Compared with a random object-related storage place; the DOMe has a standardised structure (Figure 1.2) that is divided into blocks. This structure is called the object memory model (OMM) and it is a World Wide Web Consortium (W3C) standard [Haupert *et al.,* 2011b]. A determined structure enables to personalise specific data to specified group of objects. The DOMe is both machine- and human-readable, written in the extensible markup language (XML) [Barthel, *et al.,* 2013]. It enables communication with machines and other objects that are suitably equipped. In principle, a workpiece can give orders to machine tools, create changes in the intelligent environment, capture monitoring information, organise a production plan [Li *et al.,* 2010], and order its transportation in the shop floor.

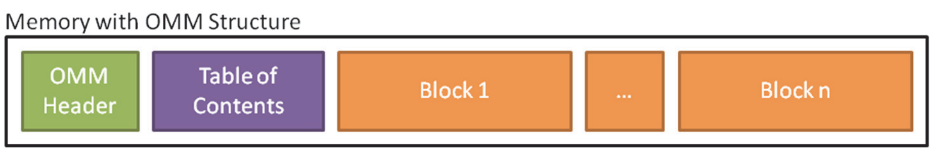

Figure 1.2 General structure of the OMM. [Haupert et al., 2011b]

The DOMe communication is mostly solved with the RFID technology but also a more expensive WSN solution has been proposed [Seitz *et al.,* 2010]. A WSN equipped object can autonomously gather, store, and analyse information but it is unwieldy and not affordable or reasonable to use for every random workpiece. Oppositely, the RFID technology enables to hold the DOMe lightweight and low cost. Passive read / write RFID tags in a sticker format can be used in low memory situations. Usually more storage space is needed to accommodate all manufacture-related data. For this reason, two types of storage space are proposed: on-board memory that is physically bonded with the object and object memory server-based memory [Haupert *et al.,* 2012] that is virtually related and accessed with the uniform resource locator (URL). Using the memory server-based solution, a RFID tag is used for identification and linking with a specific DOMe in the memory server. Besides, also mixed solutions have been proposed.

Many prototype solutions have been tested to demonstrate and design the applications. The DOMe is exploited in an advisory and controlling device of the medical pills usage [Schneider *et al.,* 2010]; in the semantic product memory (SemProM) browser to visualise memory contents in a context sensitive way according to user abilities and goals [Brandherm *et al*., 2010]; in a flexible soap filling production line [SmartFactory, 2014]; in a supply chain demonstration [Stephan *et al*., 2010].

1.5 Ongoing stimulation programs

The topic of intelligent manufacturing is highlighted all over the world. Leading developed industrial countries in the world have turned their focus onto improvements in manufacturing efficiency. They work for maintaining and recovering their competitiveness that is eroding in the manufacturing field.

In the EU, the Framework Programme for Research and Innovation drives a programme called the Public Private Partnership (PPP) Factories of the Future (FoF). The budget for the programme is EUR 1.15 billion for seven years [European Commission, 2013]. This Horizon 2020 programme aims to support technologies that increase manufacturing enterprises' competitiveness and sustainability through development of adaptive and smart manufacturing equipment and systems.

The European horizontal technology platform *Manufuture* aims to create synergy in technology-specific action plans and technology platforms between member states. Its main pillars are connected with industrial innovation. [*Manufuture* platform, 2014.]

In Germany, improvements in manufacturing methodology and technological bases are supported by a national programme called Industry 4.0. The budget for this government driven program amounts to EUR 500 million over three years. It is believed to increase industrial productivity by up to 30% [Nikolaus, 2013]. The idea is to achieve it by the growth of flexibility, integration of more intelligent high-tech IT solutions, and real-time feedback. Smart, green and urban productions are promoted for this programme. Its main idea is to develop further a concept of the so-called Smart Factory that bases on the IoT and CPPS.

The Smart Manufacturing Leadership Coalition (SMLC) in the USA is a non-profit organisation of different industrial manufacture-related interested parties. The SMLC aims to develop an infrastructure that is called the Smart Manufacturing Platform. [SMLC, 2014.]

In developed countries, there are different programmes and initiatives to support the development of smart factories in order to increase the manufacturing productivity through flexibility and better communication solutions. They all look at the problem with a little different angle but the main idea is the same – to increase the production efficiency by developing an intelligent manufacturing environment by using state-of-the-art technological bases.

1.6 Objective of research

The main problem as an indicator for research is the changed production environment with small batches, many similar one-offs, and frequent modifications of products. This environment requires high flexibility with fast and knowledge-based decisions to avoid decrease in productivity. Conversely, increased flexibility and interoperability can be seen as the next generation's success factors in industrial SMEs.

The main objective of research is to study and develop monitoring of machining processes, focussing on SMEs. The specific aims are to develop methodology for analyse machine tools status in real time, elaborate a demonstrator toolkit for testing the methodology, and find novel tools for automatic real-time monitoring in machining.

The main activities of research are:

- to research and develop an approach for planning and structuring for monitoring of machining processes, based on in-process signal and wireless communication;
- to measure, analyse, evaluate, and compare machine tool working mode and machine tool status monitoring experimental data gathered in the Department of Machinery in the TUT (Tallinn University of Technology) and in private companies;
- to develop, design, and construct a machine tool status monitoring demonstration toolkit with real-time GUI;
- to work out a concept for the RFID- and DOMe-based automated tracking solution integration into part machining performance monitoring system.

The idea is to integrate wireless sensors and RFID-based solutions with the manufacturing environment to achieve Web-based monitoring for all interested parties without the installation of cable networks. Real-time information for manufacturing-related interested parties helps make fast knowledge-based decisions, decrease scrap, avoid unplanned pauses, analyse performance, save processing time, increase sustainability, and proactively fulfil customer needs.

2 METHODOLOGY OF REAL-TIME MONITORING APPLICATIONS IN THE SHOP FLOOR

Fluent workflow in the shop floor creates bases for high productivity. Availability of clear knowledge-based information improves planning and utilisation of manufacturing processes. The purpose of monitoring is to avoid failures and achieve seamless, high-quality workflow. Information can be collected through monitoring modules and distributed according to monitoring cycles for every interested party. To develop efficient monitoring modules, a value-centric approach according to the manufacturing particularity must be utilised. The monitoring system is divided into modules to enable step-by-step implementation. Sensor equipped machine tool components, a sensors equipped cutting tool, a DOMe-equipped workpiece and the intelligent environment create broad-based synergy in the monitoring system.

2.1 Monitoring cycles for performance improvement

Productivity growth in the shop floor depends on the rate of losses in machining. According to the overall equipment effectiveness (OEE) eq. (2.1) [Nakajima, 1988], machining has three categories of losses: downtime loss, speed loss, and quality loss. Downtime loss is comprised of equipment failures, material shortage, and changeover time. Speed loss comprises machine wear, substandard materials, lower feed rates, and operator inefficiency. Quality loss is the loss of reworking and remanufacturing. In addition to productivity, the quality loss epiphenomenon is material loss. Eliminating the losses paves the way for seamless and efficient workflow. The OEE can be expressed as:

$$OEE = A \times P \times Q, \tag{2.1}$$

where A is machine tool availability (%), P is machine tool performance efficiency (%), and Q is product quality rate (%).

Relevant monitoring information must be distributed to every interested party in the shop floor, in the office, and in networked companies (service providers) to increase the overall efficiency. Downtime loss can be decreased by a mechanic, quality loss can be decreased by an operator, and speed (productivity) loss can be decreased by a production manager. Different parties need different monitoring information but their entire contribution is addressed to increase the efficiency of the enterprise, especially through their input for activities in the shop floor. According to a developed concept, “Monitoring cycles for performance improvement” (Figure 2.1), the main interested parties are the mechanic, operator, production manager, and the top manager. Every one of them has their main task that is fulfilled in the best way based on relevant monitoring information.

In many cases, in SMEs where a mechanic is rarely needed, machine tools maintenance service is ordered from a networked company. Based on the condition monitoring data, maintenance is scheduled and realised when it least affects everyday manufacturing. This is the base for machine tools availability for manufacturing. The second circle is the quality circle that works on real-time machining data. During the machining process, the operator can execute real-time control and make improvements as changes in the feed rate, cutting speed, cutting tool or stop of machining. The third cycle is based on both real-time and dataset-based information. This is called productivity monitoring; it helps production managers improve productivity. The last cycle can be called the efficiency cycle. An input for this cycle is mainly its status monitoring dataset-based information that helps the chief executive officer (CEO) make long-term decisions, such as machine tool purchases and movement to another building or location. Interested parties, mentioned in the cycles, are not eliminated from their neighbour cycles. Shared competence with expanded knowledge creates bases for the best decisions. The operator supports the mechanic with additional observations. The production manager supports the operator and vice versa. The CEO can intervene in case of productivity questions and needs feedback from the production manager for long-term decisions.

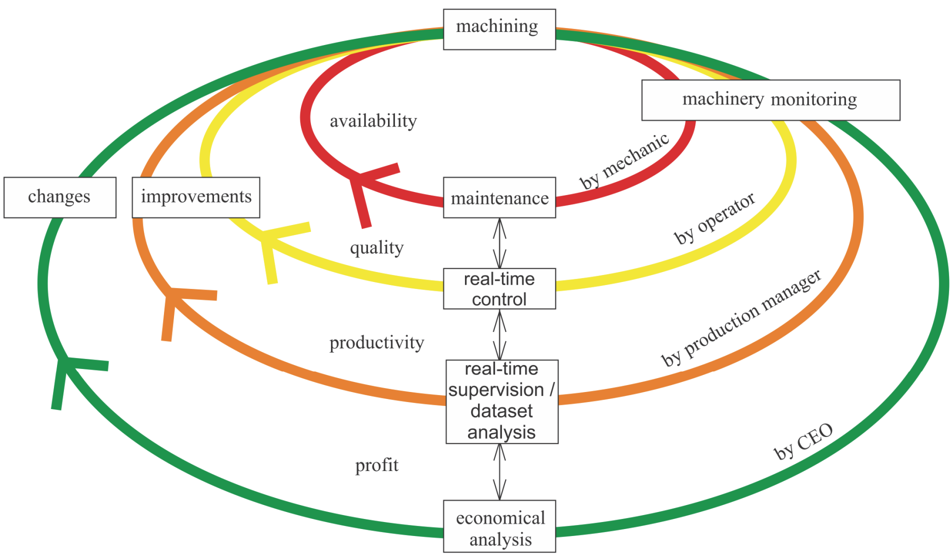

Figure 2.1. Monitoring cycles for performance improvement

2.2 Monitoring application requirements and design

On the usual line, SMEs deem to be reasonable to adapt a monitoring system step-by-step due to limited budget. As the monitoring system should be affordable also for SMEs, a large monitoring system is divided into applications that can detect and track specific machining related information. Monitoring can be adapted in manufacturing bottlenecks or in most critical processes at first and expanded over time. Knowledge-based feedback, such as output from monitoring applications requires value-centric and explicit evaluation of requirements as the bases input for monitoring modules design.

To design an efficient system, at first there is a need to define various background information to value-centric approach [Randmaa *et al.*, 2011] to keep the focus on the core problem. Background information comprises the following definitions: the objective of the observable section (1); the core problem in the observable section that breaks its objective (2); solution to eliminate the defined problem (3); objective of the solution (4); requirements for the solution (5); constraints of the solution (6).

The observable section in this case is the manufacturing section as the core of the manufacturing company participating in the supply chain. The problem definition should be explicit and not list several manufacturing shortcomings but focus on the core problem that works against the defined objective. The solution should reflect the defined problem. The objective of the solution should define what will be improved and how. All the requirements related to the solution should be brought out to keep the system vital and beneficial. Also, the inputs and outputs with other systems must be taken into account to fit the solution into the existing environment. Missing of some key factors may cause withdrawal of the solution by the interested parties. Constraints must avoid conflicts of the solution with existing systems.

The background information for the manufacturing monitoring system is defined as follows:

(1) maximise the productivity of the shop floor (supply chain);

(2) lack of real time information about processes inside a factory and in the supply chain;

(3) real-time feedback to interested parties in every process;

(4) maximise the performance of the supply chain by providing tailored real-time information to every interested party;

(5) automated, compatible, flexible, cognitive, service-based, trustful, nonintrusive, safe, easy to install, intelligent, semantic, fast, affordable, mobile, tailored, goal oriented; future oriented, proactive, low power designed;

(6) must not interrupt with the existing systems or processes in the supply chain.

Next, one by one, the value-centric solution (application) requirements are listed, analysis is performed and possible technical solutions are proposed.

- Automated – automated feedback is faster and at the same time excludes options to manipulate with information. For example, it could be beneficial for the operator to show machine tool cutting time longer and set up time shorter to point on his professionalism. Therefore, sensor-based monitoring is preferred to manual feedback.
- Compatible – in different companies within the supply chain, different hardware and software combinations are often used to collect, analyse, and

store information. Today, the biggest problem from the ICT perspective is lack of compatibility between different manufacturers' solutions. Therefore, it is essential to use standard solutions, which are supported by many producers to easily extend the system. Open source software is preferred.

- Flexible – easy to make corrections in the structure and analysis.
- Cognitive – appropriate information should be easy to find. The user interface (UI) should be user friendly and easy to adapt to make it usable. Data analysis should be at the level which is most informative but easy to catch.
- Tailored – all UIs should be tailored to the specific position in the supply chain and in company. Everybody should get access to only such information that is important for their tasks.
- Safe – it means safe for the environment, personnel, and company. Its ecological footprint should be minimised. It should not contain tasks that can harm personnel, like the need to observe a cutting tool too close while it is working. Moreover, information must be protected. Every company in the supply chain must be able to decide (and change, if necessary) which data is available over the supply chain or for a partner company.
- Service based – interested parties can be considered as service providers who act based on real-time information.
- Trustful – displayed data should be reliable and analysed using working solutions. If the algorithms are not working correctly in the controlled environment, they should be eliminated for the period of testing. Only partly working algorithms are causing frustration for their users and diminish applications' overall reliability. As machine tools are in operation, metal parts in the environment and electromagnetic waves can cause interferences with the wireless signal distribution, router nodes must be used, where necessary, to guarantee the information flow.
- Nonintrusive – redundant messages from the system slow down the speed of the work rather than create extra value. Alarms and messages should be sent to the interested party only, on time and with valuable information.
- Easy to install – eliminating wires all around the shop floor and on machine tools that may interrupt logistics and machining. PnP type solutions are preferred.
- Intelligent – collected data should be transferred to knowledge, before displaying it to the interested parties.
- Semantic – focus must be on the meaning of the data, not on the process of collecting it.
- Fast – it has to be based on real-time information. Even real-time information has always some delays. However, if the delay is short enough and does not blur the meaning and relevance of information, it is allowed.

- Affordable – relatively cheap to install and run. Short enough payback time to attract SMEs.
- Mobile – data must not be available in the exact workplace only but it should be possible to get access everywhere through mobile devices (smart phones, tablets, different smart wearable devices), which are connected to the Intranet or Internet. Basically relevant information should be available for any specific user anywhere, anytime, using any device.
- Goal oriented – specific, well-functioning task has to be on focus. Additional functions can be added or provided that do not harm the main focus.
- Future oriented – ready for expansions. It must take into account further developments in the shop floor and support the vision of a company.
- Proactive – data can be split into three main categories: historical (dataset), present (real-time), and future (forecasting) data. Historical and present data can be used as 100% trustful data (based on the belief that methods for capturing and analysis a data are adequate). Forecasting is based on a dataset which is analysed in a certain context that best describes oncoming events. The oncoming events that can harm a production, such as reaching cutting tool or some machine tool part critical wearing level, should be proactively predicted to prevent unplanned pauses and defective products.
- Low power designed – energy consumption rate determines the maintenance period of wireless monitoring devices. In wireless nodes, communication is the major energy consumer. Therefore, it is essential to analyse the collected raw data in a node on-board processor and send out only processed data. Moreover, the load in the radio frequency (RF) channel is lower and channel overload can be minimised. In energy consumption perspective, other important factors are processor type choice and hardware / software interaction [Karakehayov, 2006]. RFID tags can be active, battery-assisted passive or passive. Active tags use on-board energy source and periodically transmit identification (ID) signal. Battery-assisted passive tags use on-board battery only in reader presence. Passive tag integrated circuit (IC) is powered by a RFID reader through a RF channel.

2.3 Machining process monitoring modules

For a more flexible adaptation of the monitoring system in the shop floor of SMEs, modularisation of monitoring applications has proposed. It allows beginning with the most necessary monitoring module for every specific company and to continue expansions of the system in time. A large system is more complicated to handle and often creates economic and also psychological barriers in its adaptation.

Machine tool-related monitoring applications are divided into five modules according to their features. These modules are machine tool health monitoring, status monitoring with pause reasoning, cutting process working mode detection, tool insert life monitoring and part quality monitoring with on-board data storage (Table 2.1). These modules are directly related with machine tools but the system can comprise also other shop floor-related monitoring applications as material flow tracking, worker tracking, manual work station monitoring, etc.

Table 2.1 Utility of machining processes monitoring modules
CAD (computer aided design), CAM (computer aided manufacturing)

Monitoring module	**Information type**	**User**	**Changes**	**Utility**
Machine tool health monitoring	Dataset	Mechanic	Well-timed maintenance and components replacement	1. Avoidance of unplanned pauses 2. Better machining quality 3. Maximum utilisation time of components
Status monitoring with pause reasoning	Real-time/ dataset	Manager	Better situation awareness about rate of utilisation, setup time, idle time with specific reason, and failures.	1. Better planning of sales and shifts 2. Operators comparison based addressed training 3. OEE feedback 4. Jigs ease of use 5. Improvements in CAD/CAM files, in work orders flow and in raw material availability
Working mode detection	Real-time	Operator	Cutting input parameters change/ stopping of machining	1. Improvement of parts quality 2. Decrease of reworking 3. Material saving
Tool insert life monitoring	Real-time	Operator	Well-timed replacement of tool insert	1. Better machining quality 2. Maximum utilisation of tool insert
Part quality monitoring and data on-board storage	Real-time	Operator	Automated quality check	Every part is considered as unique

2.4 Status monitoring and pause reasoning

For productivity analysis, machine tool status analysis is a tool of high importance. Status analysis gives basic information on whether a machine tool was working within a certain time frame. Furthermore, pause reasons identification analysis is a tool for improving utilisation in the future by learning from previous mistakes. Continuous work with status and pause identification analysis gives input for the improvement of decisions and productivity growth. Status monitoring is also an input for the OEE and total effective equipment performance (TEEP) calculation.

Compared with other monitoring modules, status monitoring with pause identification is relatively easy to deploy. The results are clear and their utility is high. Additionally to full-scale productivity, it helps to analyse every particular workbench, every particular operator and also quality of other workbench servicing sections as maintenance, production planning, material purchasing, designing and engineering. If one of the servicing sections fails, workbench cannot be used. The monitoring brings out shortages in cooperation between sections and characterises their efficiency.

In status monitoring, it is important to distinguish machining and stand still. The main engine working does not mean productive work yet. It only shows that the operator has arrived. For example, in lathe, spindle engine or spindle related parameters need to be measured. It allows to measure every cycle time and separate set up times.

At present, most of the machine tool manufacturers add a status monitoring log to the machine tool. The machine tool processor stores the start and end time of every working cycle with a working file name. It is displayed in a table format and is not available over the network to all interested parties. The shortage is that every machine has to be analysed only in a particular working place. Besides, due to different monitoring logic approaches in different machine tools, their utilisation cannot be compared among each other. It does not give an overall picture and is complicated to use for the production manager. It is essential to gather utilisation data into one database. Besides, the monitoring logic approach needs to be uniform over the shop floor or even larger entity.

2.5 Tool insert life monitoring and surface quality influence

The condition of cutting tool insert is continuously changing input parameter in machining. It forms a part surface and it has direct contact with a workpiece. The tool insert wearing level has a significant influence on the machined part surface quality. Usually, cutting tool producers give an estimated life for tool insert but it is valid only with certain cutting input parameters and with certain workpiece material hardness. Harsh, but also too weak cutting parameters speed up the wearing. Furthermore, there are different wearing types and these all have different physics influencing the turning [Otto *et al.*, 2003].

Taylor tool life equation, eq. (2.2) [Taylor, 1907], is a widely known model for tool insert life detection. It can be expressed as:

$$v \times T^{\eta} = C_1, \tag{2.2}$$

where v is cutting speed (m/min), T is actual cutting time required to dull tool (min), η is exponent which varies with workpiece material and cutting tool and C_1 is a constant which depends mainly on the size of cut, workpiece material and cutting tool.

Nevertheless eq. (2.2) does not take into account many less significant influencing parameters, such as the feed rate, depth of a cut, or fluctuating parameters. There is also a more advanced extended version of the Taylor equation, eq. (2.3) [Woldman *et al.,* 1951] that can be expressed as:

$$v \times T^{\eta} \times f_c^{y} \times d^{x} = C, \tag{2.3}$$

where v is the cutting speed (m/min), T is the actual cutting time required to dull a tool (min), η is an exponent which varies with the workpiece material and cutting tool, f_c is the feed rate (mm/rev), d is the depth of the cut (mm), C is a constant which depends on the work material and tool, x and y are exponents which vary with workpiece material and cutting tool.

Equation (2.3) involves more parameters than eq. (2.2), but its disvalue is a high number of constants. On the one hand, the number of constants increases the accuracy but, on the other hand, a rough estimation of constants can conversely decrease the accuracy.

There are many more probabilistic tool life models based on response surface methods. Nevertheless, there is no good model that is efficient, reliable and applicable in real-time in-process monitoring [Stephenson *et al.,* 2006]. One option is to study the cutting insert reliability but it is time consuming and needs a large number of samples that are limited due to tool insert's relatively short life.

In stable working conditions, tool inserts wearing level is linearly related to the machined parts surface roughness. The theoretical depth of surface roughness, eq. (2.4) (Figure 2.2), that can be easily found characterises only the ideal condition that never appears in the shop floor. It can be expressed as:

$$Rz_t = {f_c}^2 \times \frac{1000}{8 \times r_E}, \tag{2.4}$$

where Rz_t is the theoretical ten-point mean roughness (µm), f_c is the feed rate (mm/rev), and r_E is tool insert's nose radius (mm).

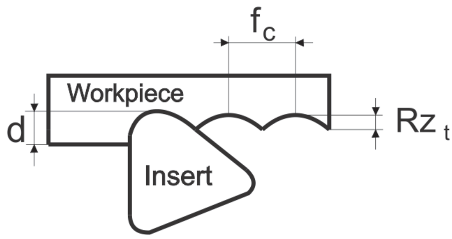

Figure 2.2 Theoretical surface roughness in turning

The equation does not take into account machine tool's instability (rigidity level) and material type. It also does not take into account that inside the linear relationship there can be quite powerful fluctuations caused by material heterogeneity and elastic / thermal deformations [Aruväli *et al*., 2014].

Fluctuations and other related parameters influence the behaviour of the tool insert – workpiece contact point. According to Huang, the feed rate and vibrations have the biggest influence for part surface roughness [Huang *et al.,* 2001]. Feed rate is covered in eq. (2.4) but additional in-process vibration / acoustic signal features, eq. (2.5), makes the model more accurate and practically usable. It can be expressed as:

$$Rz_s = {f_c}^2 \times \frac{1000}{8 \times r_E} + S_f \times C_c, \tag{2.5}$$

where Rz_s is the in-process signal-based estimated ten-point mean roughness (µm), f_c is the feed rate (mm/rev), and r_E is tool insert's nose radius (mm), S_f is the in-process signal feature, and C_c is a constant which depends on in-process signal features.

Tool insert – workpiece contact point carries the most sensitive data [Waschkies *et al.,* 1994] that best characterises the in-process cutting quality. The cutting tool insert with a tool holder is the closest component to the cutting point. Therefore, placement of vibration and acoustic sensors inside the tool holder should be preferred to collect cutting in-process signal. It eliminates the need for manual installation of sensors. There is no need to make changes in the machine tool to implement it either. As changes in machine tool are related to machine tool manufacturers and history has shown that fast changes are not expected by manufacturers, an intelligent cutting tool holder is a more valuable solution. Parallel can be drawn with the Step NC compliant machine tool development. There has already been more than 15 years development and standardisation in the area of the Step NC compliant machine tool but no supply of these machine tools is recognised in the market.

2.6 Digital object memory in the machining process quality monitoring

In the shop floor, experiments have been made to manufacture mostly module-based products in the manufacturing cell [SmartFactory, 2014]. It is valuable for companies with a limited product range. However, these experiments do not cover, for example, subcontractors that manufacture a continuously changing range of products. Machinery industry mostly uses machine tools with a G-code input. The problem is that G-code requires more storage space than just a work number for the controller of manufacturing cell module. DOMe-based monitoring processes have not been studied by researchers so far, just production time collecting has been implemented. However, for automatic real-time machining process's quality monitoring, the machining in-process signal has to be evaluated. This is an indirect measuring method and is not as accurate as the direct measuring methods but is less time consuming and enables to give real-time feedback.

A concept for RFID-based DOMe usage in part quality monitoring through machining process performance real-time evaluation [Paper IV] has been developed and proposed. The concept covers three artefacts (smart objects): the workpiece, the machine tool, and the cutting tool. All these artefacts are equipped with communication appliances (DOMe) and located in the intelligent environment.

Machining, assembling and stock areas are like intelligent environment islands in CPPS. Meaning, these areas are equipped with a RFID reader, necessary number of antennas and a context-based semantic [Croisier, 2012] back end system.

Context- and rule-based data sharing between the workpiece, cutting tool and machine tool composes bases for a particular in-process signal evaluation. Researchers have worked out different models and algorithms for workpiece surface finish and machining process quality measurement. Besides in-process signal, important input for most of the algorithms are cutting parameters as speed, feed rate and depth of cut; machine tool coefficient; workpiece material hardness; tool insert radius. All this information is covered by the mentioned objects (Figure 2.3). The machine tool sends its coefficient, cutting tool its insert radius and workpiece its diameter, material hardness and G-code related cutting parameters.

As workpiece needs to carry G-code information for machining input, it can be used simultaneously in monitoring appliances. G-code covers information such as the cutting speed, feed rate, depth of cut, number of cuts, cutting tool number for particular cut, cooling liquid usage. Having DOMe information from all three cutting related artefacts and cutting tool sensors measurements, it is possible to distinguish between different cuts during one operation, select a suitable pattern for monitoring, and indirectly measure quality-related parameters such as cutting mode, part surface roughness [Paper IV], and cutting tool's end of life.

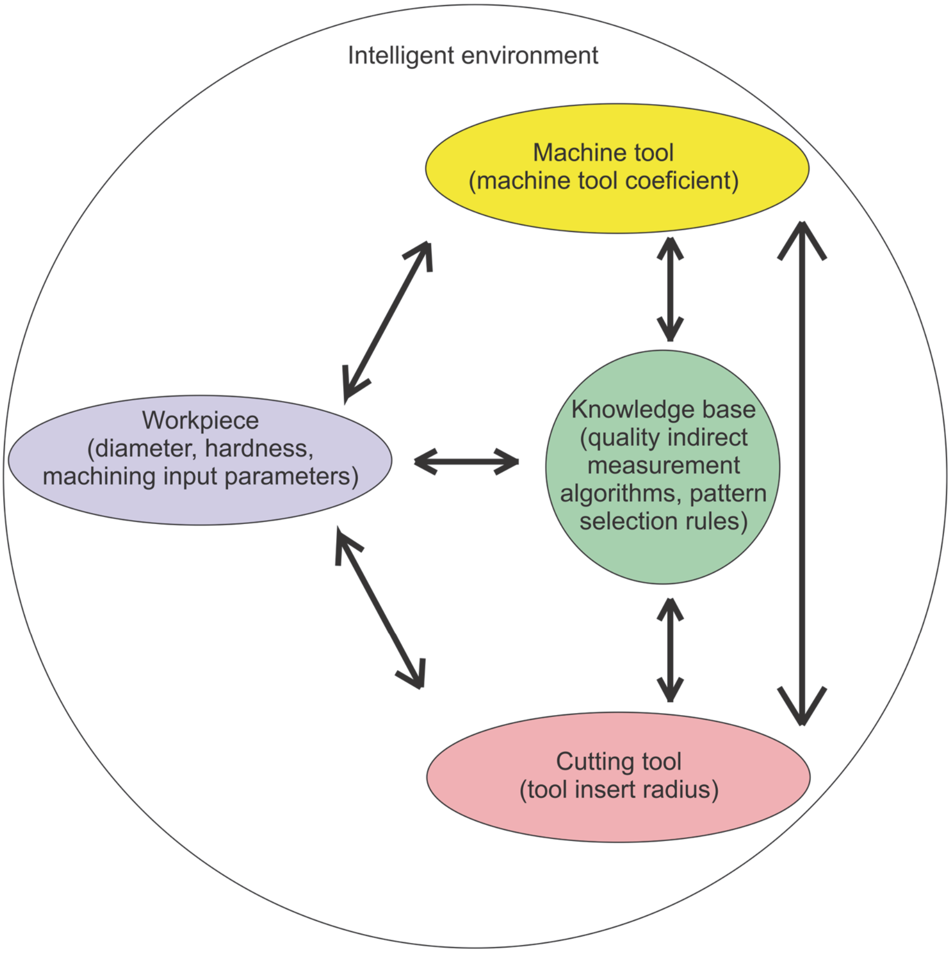

Figure 2.3 Communication in intelligent environment of machining unit

Researchers have carried out several successful experiments for quality parameter real-time estimation that can be used in the machining spot intelligent environment. In cooperation with DOMes, providing input data for algorithms, comparative quality parameters can be evaluated and stored (Figure 2.4). Many of the ANN and regression analysis based algorithms have been proposed (Chapter 1) that can be utilised in a DOMe based solution.

DOMe based quality monitoring scheme works as follows. When a cutting tool is taken from the carousel and brought to the cutting position, intelligent environment activates schema. At first, relevant information is asked from all related objects (machine tool, cutting tool, workpiece). Simultaneously, cutting tool sensors are woken up and the first signal frame is collected. Every signal frame is first processed in the cutting tool processor to evaluate whether cutting has started (the signal frame value is bigger than defined 0-value). An analogue signal is converted to digital. According to the cutting input parameters, a pattern for evaluation is selected and previously digitalised data extracted to evaluate and store in-process quality parameters. Immediately after every parameter saving, it is displayed directly to the operator. In process real-time knowledge base feedback gives operator the opportunity to make fast changes in the manufacturing process, if needed. Thereafter, a new frame is gathered and the loop starts again until a signal shows the end of the particular cut. After every cut, quality parameters, stored in intelligent environment memory, are sent to the workpiece DOMe. Successful response from the DOMe means that parameters can be deleted from the environment memory.

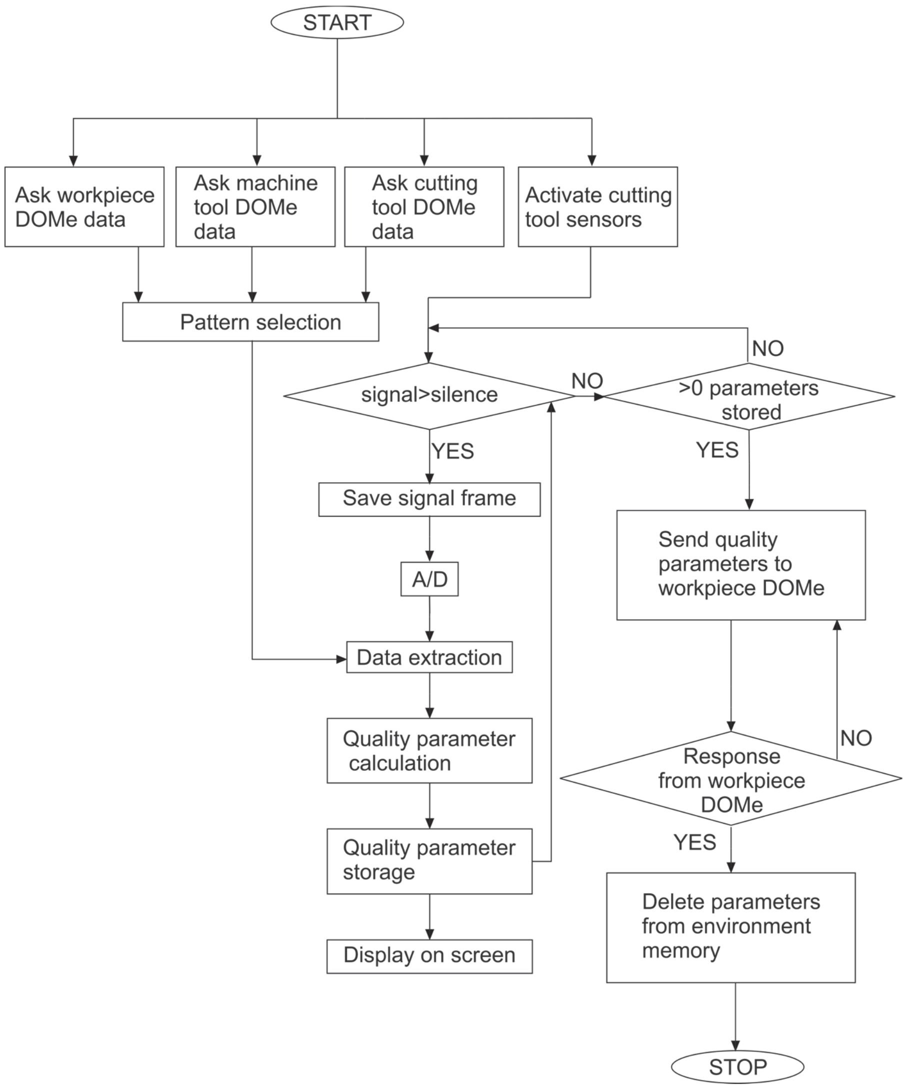

Figure 2.4 DOMe driven monitoring scheme in machining

3 EXPERIMENTS AND PROTOTYPING

Working mode detection, failure detection and status monitoring experiments were implemented in the Department of Machinery of the TUT and in private companies. Working modes and failure situations were studied through vibration- and acoustic-based measurements. Machine tool status was detected through current consumption, vibration and acoustic measurements. Experiments show high reliability in machining processes monitoring. Additionally, a prototype demonstration toolkit for machine tool status monitoring and pause reasoning with real-time GUI was developed and constructed. Most experiments were implemented using a wired solution but all measurement devices were chosen according to further usage in the wireless solution.

Working mode and failure situation detection in turning is analysed using time domain in acceleration signal and frequency domain in acoustic signal. Additionally optimum measurement frequency and number of successive measurement values were found in in-process acceleration signal. Status monitoring acoustic and acceleration signals are analysed using feature extraction methods, such as Mel-frequency cepstral coefficients (MFCC) and spectral means.

3.1 Working mode estimation and failure detection

Real-time working mode monitoring is essential for a machine tool operator to be fully aware of the cutting process in every moment of time. Real-time knowledge-based feedback gathered with acoustic and acceleration sensors gives more reliable feedback than old-fashioned visible observation, perceptible sound, or sensed vibrations. Real-time reliable feedback allows the operator to make fast changes in machining input parameters to increase the part surface quality and cutting tool life through improvement of the working mode.

The proposed machine tool working mode monitoring module can be implemented both in new machine tools but also in old machine tools. 30 – 40 year-old machine tools are typically massive and rigid. These machine tools efficiently suppress vibrations and can assure stable machining. These machine tools can be valuable for many more years. Their main disadvantage is their lack of monitoring functionality. Equipping them with modern monitoring appliances lengthen their life cycle and at the same time this is environment-friendly behaviour and increases sustainability.

In the same way, low-budget new machine tools are equipped with no monitoring appliances. In many cases the manufacturing equipment can harm itself either because of a wrong mode of operation or trivial component failures without any advance indication of potential problem from the on-board monitoring system. Hence, operation in an undesirable mode is a potential source for the lack of part quality; raw material perversion; unplanned pauses; machine tool and cutting tool damages.

In next experiments, turning with cutting input parameters recommended by the tool manufacturer is considered as a stable working mode. Turning with higher speeds and depth of cut is considered an unstable working mode.

3.1.1 Acceleration signal-based failure detection

Experiments to distinguish a tool failure from a stable working mode were conducted on the CNC lathe 16A20F3RM132 in the Department of Machinery of the TUT [Paper I]. Acceleration of the unit was measured with the three-dimensional MEMS accelerometer LIS3LV02DQ. The data acquisition (DAQ) device Atmel AVR XMEGA was used. A sampling frequency of 640 Hz was chosen. Experiments were implemented using a wired solution but all measurement devices were chosen according to further usage in the wireless solution. Results were analysed in a time domain using range values of signal frames.

The range value of acceleration signal frame characterises vibrations during the cutting process. It is known that in a stable working mode, vibrations are smaller and they increase in unstable machining. The range values of acceleration were found for every test and compared as eq. (3.1):

$$R = x_{max} - x_{min}, \tag{3.1}$$

where R is range, x_{max} is the maximum value and x_{min} is the minimum value in observed signal frame.

According to the range values of acceleration signal in turning, it can be seen that spindle's idle turning and stable cutting mode are similar. However, the range value increases in a failure situation, especially in y-axis. Thus, a failure situation can be detected from a stable working mode.

The graphical representation of acceleration signal shows visible difference between a stable turning and turning with a failure that ended up with tool breakage. These comparable tests have been made with the same cutting speed (180 m/min) and feed rate (0.3 mm/rev). A difference was in the depth of cut that occurs with a failure in a higher value. Tool breakage at a higher cutting speed (723 m/min) generates unbalanced acceleration / time graph.

The comparison of the acceleration signal range values in y-axes enables to distinguish failure from stable cutting mode (Table 3.1).

Table 3.1 Range values in stable cutting and in failure situation

Spindle speed (min^{-1})	Feed rate (mm/rev)	Cutting speed (m/min)	Failure	R_{x-axis}	R_{y-axis}	R_{z-axis}
600	0.3	180	No	125	161	89
600	0.3	180	Yes	133	200	94

3.1.2 Acoustic signal based failure detection

Experiments to distinguish tool failure from stable working mode were conducted on the CNC lathe 16A20F3RM132 in the Department of Machinery of the TUT [Paper I]. The acoustic of the unit was measured with the SM58 microphone. Roland's Edirol UA-25EX audio signal processor was used. Sampling frequency 22050 Hz was chosen. In-process audio signal was recorded through different working modes (main engine working, spindle idle turning, stable working mode and failure). Signal frames were analysed in the frequency domain using spectral analysis. Experiments were implemented using wired equipment but the results characterise the leverage of acoustic signal analysis.

After the fast Fourier transform (FFT) according to sample frequency spectrums of signal frames, it can be concluded that spindle's idle turning and stable working mode are not distinguishable. However, main engine's working, a stable working mode and a failure situation are distinguishable.

3.1.3 Acceleration signal-based working mode detection

Experiments to distinguish an unstable working mode from a stable working mode were conducted on the CNC lathe Okuma OSP 2200 in a private metal working company [Paper II]. Additionally, optimisation of sampling frequency and signal length were performed to minimise energy consumption and maximise the speed of feedback. Acceleration of the unit was measured with the three-dimensional MEMS accelerometer LIS3LV02DQ. The DAQ device Atmel AVR XMEGA was used. Seven different sampling frequency, spindle speed and feed rate level combinations were tested. Tests 1 – 3 were performed in a stable working mode (cutting input parameters near the lower limit recommended by tool insert producer), tests 4 – 6 in an unstable working mode (cutting input parameters over the upper limit of recommendation) and test 7 with spindle idle turning. Results were analysed in the time domain.

The number of measured sample values in an analysed signal frame influences feedback time and computational operation efficiency. On the one hand, the more samples are gathered into the signal, the more reliable the result is. On the other hand, the longer the signal, the slower the feedback is. As raw material can be ruined within seconds, it is important to get fast feedback about ongoing machining to stop or change the current process, if needed. To find the optimal signal length, experiments were first analysed with 130, 260, 520 and 640 successive samples and later more precisely with 60, 100, 130 and 160 successive samples. Ten signals were studied from every length. To compare and evaluate the results, restrictions were created. To analyse signals reliability, three parameters were compared: arithmetic mean value of range values – eq. (3.2); maximum range value of studied signals; and range value of studied range values – eq. (3.3). The arithmetic mean value of range values was found as:

$$\bar{x}_R = \frac{1}{n}\sum_{i=1}^{n} R_i, \tag{3.2}$$

where $\bar{x}_R$ is the arithmetic mean of range values, n is the number of range values, and R is the range value. The range value of the studied range values was found as:

$$R_R = R_{max} - R_{min}, \tag{3.3}$$

where R_R is the range of range values, R_{max} is the maximum range value, and R_{min} is the minimum range value.

Acceleration signals were compared based on range values. The used accelerometer's smallest possible sampling frequency 160 Hz shows a sufficient difference between a stable and unstable working mode (Table 3.2). The smallest frequency of the used sensor was 160 Hz and due to that smaller frequencies were not tested. All axes show more than a double difference in range values. Experiments prove that a stable working mode and unstable working mode can be detected with an accelerometer and compared according to range values. Sampling frequency 160 Hz is sufficient.

Table 3.2 Acceleration range values along different axes with depth of cut 2 mm and sampling frequency 160 Hz

Spindle speed (min^{-1})	**Feed rate (mm/rev)**	**Cutting speed (m/min)**	**Acceleration range values**		
			x-axis	**y-axis**	**z-axis**
220	0.25	155	40	22	44
540	0.4	380	152	290	97

According to the analysis, 130 successive measurement values with a 160 Hz frequency were reported as sufficient. It means the signal length of 0.8 sec is optimal to detect lathe's in-process working mode.

3.2 Status monitoring

Machine tool's real-time status can be measured using various physical parameters and different sensor types. Physical parameters such as current, vibrations and acoustics can be used for status detection. Also movements in working zone can give relevant feedback. A demonstration toolkit of status monitoring and pause reasoning gives a simple and effective overview of the monitoring module. It is a useful instrument in teaching and in cooperation approach with private companies.

3.2.1 Current consumption based identification

One option for status monitoring implementation is the usage of current sensors to evaluate its utilisation through power consumption. Current sensors were used in experiment with the CNC milling machine Dyna Mechtronics EM3116 in the Department of Machinery of the TUT [Serg *et al.,* 2014]. For data acquisition, National Instruments (NI) WSN nodes, gateway and LabView programming environment were used.

Experiments prove that in milling machine distinguishing switched off, the main engine working and spindle turning statuses according current signal, is possible (Figure 3.1). Milling machine is switched off within 0 – 50 seconds, the main engine is working within a period of 51 – 180 seconds, and the spindle is turning within 181 – 330 seconds. Switching on the main engine, current consumption grows from 0 to 0.7 A. Turning on the spindle, current consumption grows near to 3.2 A. Spindle's stopping decreases current consumption to the prior level of 0.7 A.

Milling of steel S355J2 with the feed rate 90 mm/min (stable cutting mode) and spindle idle turning are visually distinguishable (Figure 3.2). The difference between current consumption is below 10 %, 3.2 A in a spindle idle turning and 3.5 A in a stable cutting mode. The threshold value between the working status and stand still can be drawn in 2 A. This position leaves a safety area in both directions of current consumption (main engine working and spindle turning situations) and results are protected against fluctuations.

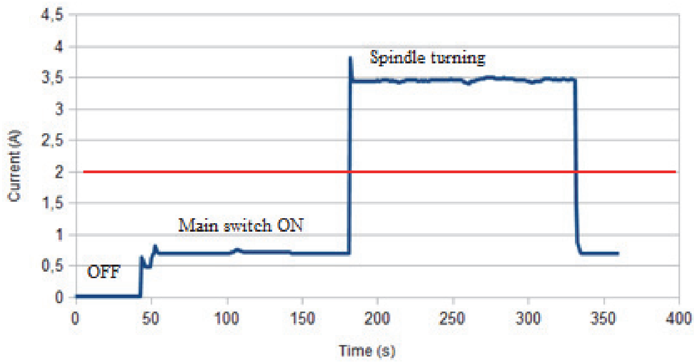

Figure 3.1 CNC milling machine current consumption in switched off, main engine working and spindle idle turning positions

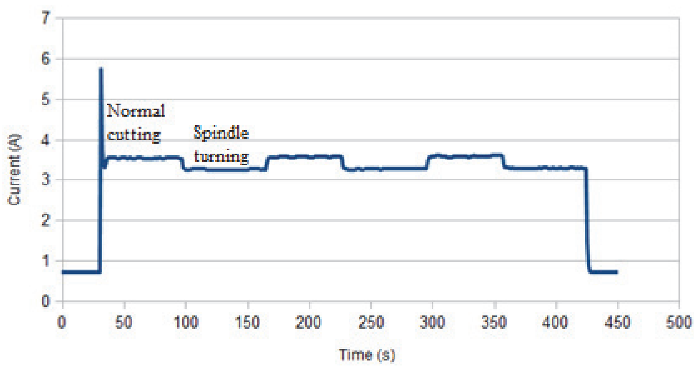

Figure 3.2 Current consumption dynamics in milling of steel S355J2

3.2.2 Single point acceleration and acoustic signal based identification

Vibration and acoustic signal monitoring experiments for machine tools status analysis were performed in the plastic working company Nordic Plast [Astapov *et al*., 2012]. The aim was to compare the reliability of status monitoring in different machine tools using different physical parameters and different analysis methods. All experiments were performed in the natural working environment. It means no machine tools were stopped to get silence during measurements. Noise can mostly interrupt acoustic measurements of relatively quiet machine tools, such as a laser cutting machine, if some noisy operation is performed nearby. Experiments were performed in the CNC laser cutting machine Vytek LST4896 and in the 3-axis CNC router AXYZ 6020.

In experiments, the CNC laser cutting machine Vytek LST4896 was used for cutting 1 mm thickness polystyrene sheet plastic. Audio signal was measured with a Shure SM58 microphone and analogue-to-digital (A/D) converted with a Roland Edirol UA-25EX audio signal processor at 44.1 kHz sampling rate in mono channel mode, digitalised data was saved to a 16 bit waveform audio file (WAV) format. Microphone was placed near the working zone (Figure 3.3). Vibration was measured with the analogue dual-axis accelerometer ADXL311. The DAQ device Agilent U2354A was used to A/D the signal at a sampling frequency of 1 kHz. An accelerometer was attached to the laser cutting machine's X-axis. All the measurements data was taken using wired solutions. Later, analysis was performed using the Matlab programming environment.

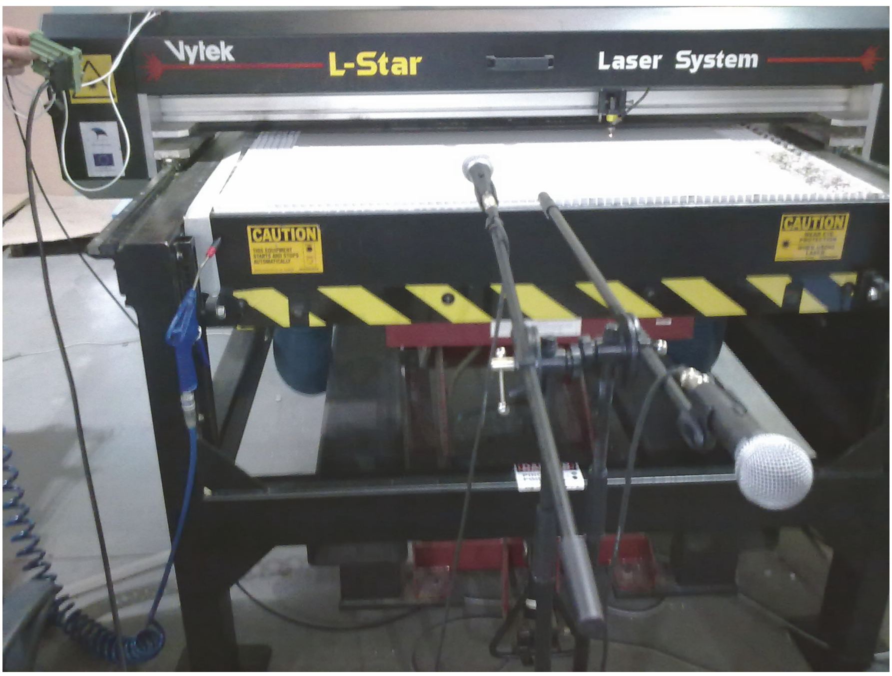

Figure 3.3 Measuring of acoustic signal in laser cutting

CNC router AXYZ 6020 was used for cutting 21 mm thickness plywood sheet material. Exactly the same measurement devices and methods were used as in laser cutting. An accelerometer was attached to the spindle.

For data analysis, two feature extraction methods were used and compared, the MFCC [Davis *et al.*, 1980] and spectral means. Both of the methods are frequency domain based and extract data from the spectrogram.

The MFCC is an often used method in speech recognition. The MFCC is type of wavelet. To calculate the MFCC, the first FFT was applied and frequency power spectrum was found, thereafter frequency was converted to the Mel-frequency scale as eq. (3.4) [Wang *et al.*, 2002]:

$$Mel(f) = 2595 \log_{10}\left(1 + \frac{f}{700}\right), \tag{3.4}$$

where $Mel(f)$ is Mel-frequency scale and f is frequency (Hz).

The Mel-frequency scale is similar with human ear, up to 1 kHz it is linear and frequencies above are logarithmic. The final step was the Mel spectrum conversion back to the time domain and cepstral coefficients were found. Discrete cosine transform was used for the conversion.

Analytical analysis method spectral means is a combination of three main steps. At first, signal frame was transformed to the frequency domain using the FFT. Then the most distinguishable frequency intervals were found and finally the mean values of the frequency intervals were calculated during the analysis and concatenated to the feature vector.

Two different class labelling methods were used for knowledge base creation: the correlation classifier and fuzzy classifier. Correlation-based classifier compares the received feature vector to knowledge based reference vectors. Every class was described with at least one knowledge-based reference vector. The highest correlation between the received feature vector and reference vector determined the class label. A fuzzy classifier also used reference vectors that derived rule base for classification. Degrees of memberships were calculated for received reference vectors to the feature subspaces. The highest membership in the feature subspace defined the class for every particular signal.

Results show high reliability in most of the analysis combinations (Table 3.3). It can be seen that an acoustic signal gives more reliable results in laser cutting. The reason is that a laser cutting machine generates a specific sound that is easily distinguishable but vibrations are low. In milling, better results are achieved by monitoring with accelerometer. The reason is that CNC router's main acoustic source is a vacuum pump that is used for fixing sheet material to the cutting table. Vacuum pump works longer than cutting lasts and can cause disarrays in analysis. Acoustic from spindle during the cutting is not that distinguishable as vibrations. The MFCC feature extraction method gives higher reliability than the method of spectral means. Both of the methods are frequency domain based and extract data from a spectrogram (Figure 3.4).

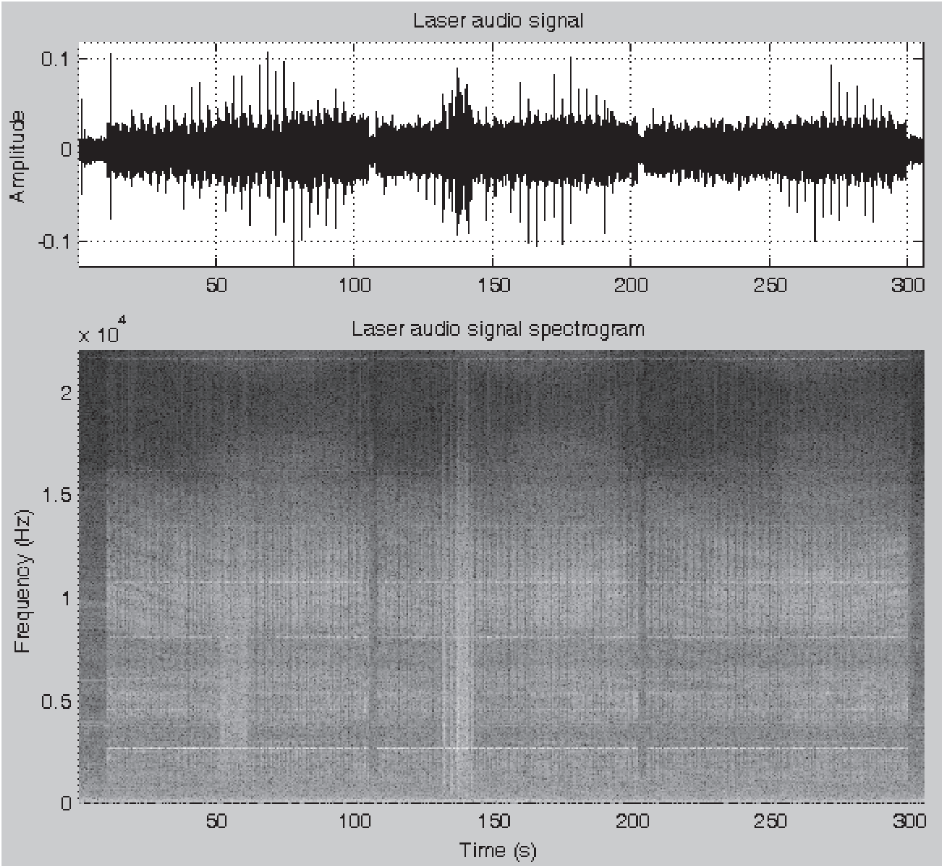

Figure 3.4 Audio signal and audio signal spectrogram in laser cutting [Astapov et al., 2012]

Table 3.3 Percentages of correctly specified signal frames

Measured parameter	Correlation		Fuzzy	
	MFCC	Spectral means	MFCC	Spectral means
Router acoustic	91.76	95.72	98.68	98.72
Router acceleration	98.39	99.85	99.85	99.49
Laser acoustic	92.68	97.56	89.02	98.05
Laser acceleration	91.80	65.80	73.40	87.65

3.2.3 Multi channel acoustic signal based identification

In the previously described machine tool status monitoring experiments only one sensor was used to collect data for analysis. Experiments with multi-channel acoustic signal analysis (microphone arrays) that form a field of view (FoW) of 15 – 25 m^2 were implemented [Astapov *et al.*, 2014] to test sensing reliability from a longer distance in the Department of Machinery of the TUT. The idea is that one set of sensors can be used to detect the status in more than one machine tool. The uppermost goal would be the detection of all machine tools in a shop floor using one set of sensors that lowers the installation cost and uniforms the solution even more. Nevertheless, efficiency growth can be achieved even using the same sensors for 2 – 3 machine tools. The other benefit is physical independency from machine tool. Moving parts and permanent vibrations are harmful for on-board microphones. Furthermore, the extra weight of nodes and sensors can unbalance a cutting tool and increase the quality of the cutting process.

Experiments were implemented on the CNC lathe 16B16T1 and on a conventional lathe. For measurements, the 16 Vansonic PVM-6052 condenser microphones were used on both machine tools. A total of four subarrays were used, every subarray has four sensors with a cap between 15 cm. The Agilent U2354A DAQ device with a sampling rate of 8 Hz was used for data collection and conversion.

For localisation, the computational load reduction in global maximum calculation is performed by an initial search region reduction. For feature extraction, indicators such as band energy, central centroid, spectral roll-off, and central slope were found. For signal classification, fuzzy rule-based classification was used. For conventional lathe measurements, microphone arrays were placed angularly (two sub arrays linearly and other two sub arrays also linearly but in 90° angle compared with first two sub arrays).

Optimised results show that linearly placed microphone arrays give reliability 90.5% in status monitoring. Angularly placed microphone arrays give reliability 94.5%. Angular placement of microphone arrays should be preferred according to higher reliability. Also observation of the steered response power (SRP) images gives visual synopsis of the machine tool status. As visual perception is intuitive and easily detectable, coloured real-time moving images such as the SRP are with high potential in machine tool status monitoring. Higher power of acoustic emission in the engine area (Figure 3.5) characterises main engine working and higher power of acoustic emission in the spindle area (Figure 3.6) characterises spindle turning.

So far, the acoustic signal is mostly captured using wired equipment as in this experiment. Acoustic signal requires a high sampling rate and sets high requirements to the WSN nodes in case of wireless monitoring. The main benefit of microphone arrays is a larger sensitive area and lack of contact from machine tools. As wireless solution's main benefit is to get rid of additional wires specially on machine tools to avoid disturbance but microphone arrays are physically disconnected from machine tools, making the data transmission wireless does not give any big effect. The problem is that so far the FOV is still relatively small and using 16 sensors instead of one is not efficient. Creating of SRP images is very calculation quantitative and expensive sensors with high sensitivity are needed for expanding the sensing area.

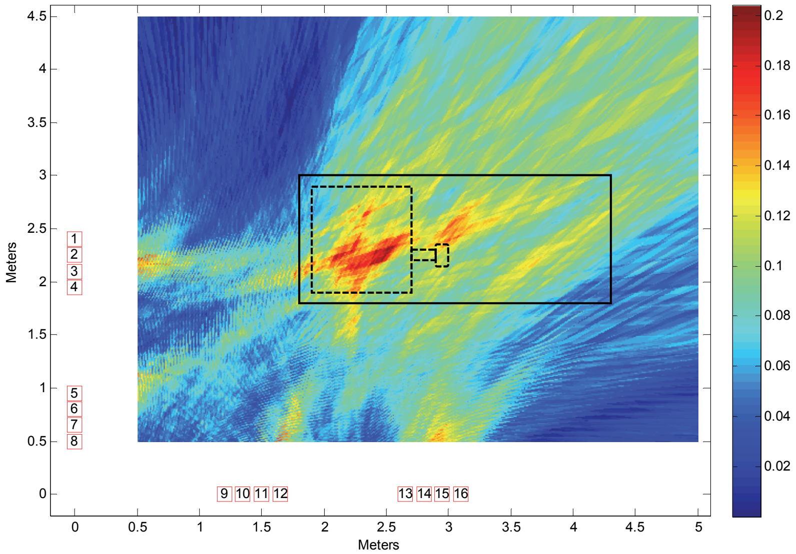

Figure 3.5 SRP image of lathe engine turned on

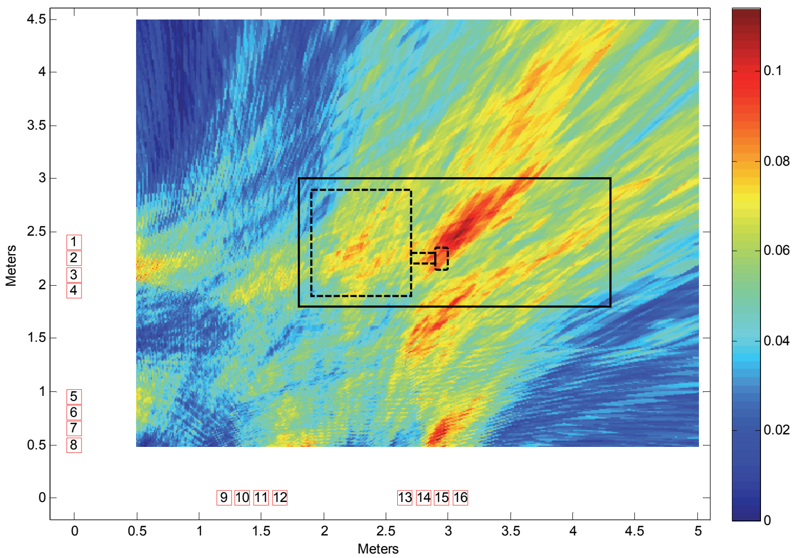

Figure 3.6 SRP image of lathe spindle turning

3.3 Status monitoring and pause reasoning demonstration toolkit

A novel machine tool status monitoring demonstration toolkit prototype was developed and constructed using NI WSN software and hardware components to introduce and evaluate machine tools status monitoring importance [Paper III]. There were two main reasons for the demonstration toolkit development and construction. The first purpose was to test developed solution's feasibility. The second reason was to introduce and illustrate machine tool status monitoring application for students and also manufacturing related persons to popularise the usage of machine tool status monitoring. The aim was to show how simple the installation is and how much relevant real-time and dataset based information the monitoring module can collect for further improvements in shop floor.

The demonstration toolkit's main components are three old-fashioned lathe demonstration models with wireless nodes, gateway, and an industrial personal computer (PC) (Figure 3.7). Lathe demonstration model bodies are made of glossy polymethyl methacrylate (PMMA) sheet plastic to highlight the monitoring module's attractiveness. The PMMA is easy to process and light weight thermo plastic. Laser cutting, thermoforming and bonding were used to construct the lathe bodies. Front and back sides are made of black PMMA to carry along the feeling of oily machine tool. Top, left and right sides are made of clear PMMA to hold wiring visible inside the model. Bottom was open for further improvements and more curious students.

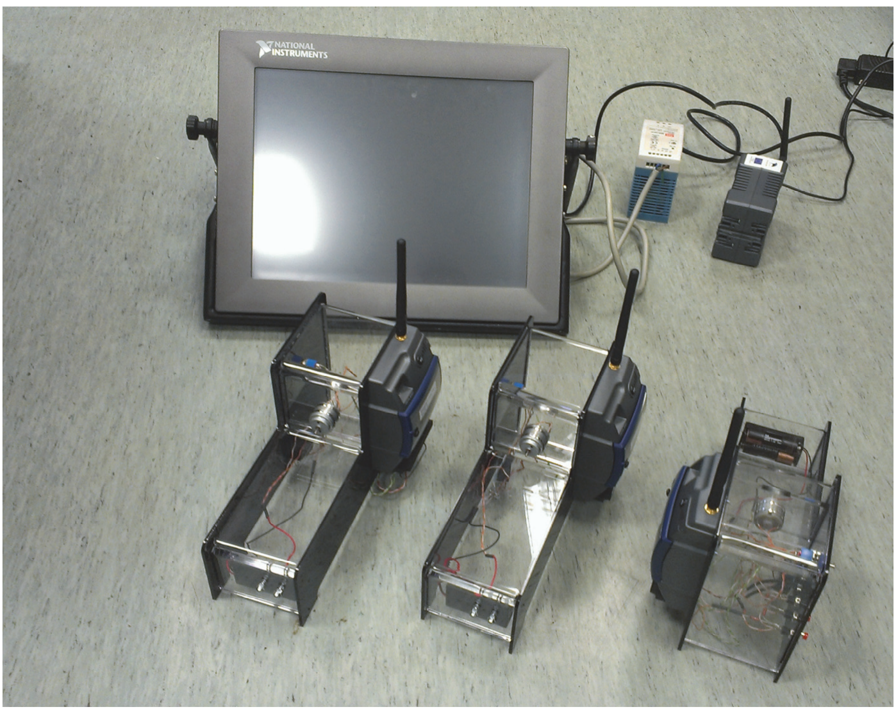

Figure 3.7 Status monitoring demonstration toolkit

Lathe models are equipped with energy source, micro motor, on / off / remote control switch, pause reasoning feedback buttons, relay, wireless communication capability (wireless node), led indicator and wiring between the components (Figure 3.8). Three AA batteries are used as energy source. Motor is installed at place of spindle to imitate turning spindle. Three position switch on / off / remote control was used. As name says, third position is remote control. It means, lathe models motors were also remotely wirelessly controlled from GUI in an industrial PC to present two directional communication.

Wireless communication is driven by the NI WSN 3202 that uses a RF channel to communicate with the NI gateway 9791. The gateway is connected with the PC via an Ethernet cable.

Voltage is the sensed phenomenon. As voltage in an unpowered cable is always bigger than 0.0 V, the threshold value 0.2 V is determined between the working and standstill status.

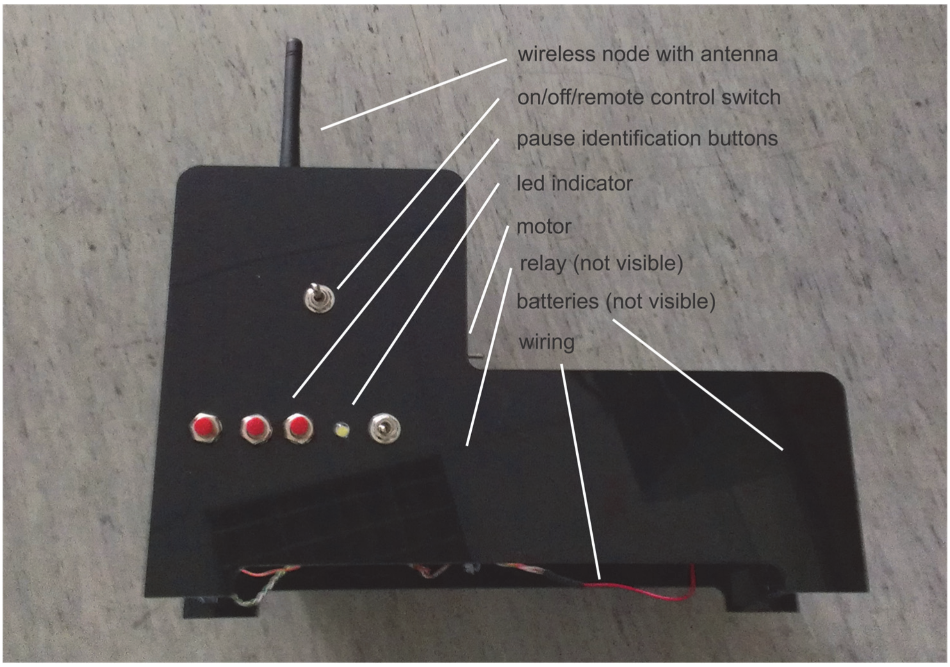

Figure 3.8 Demonstration toolkit lathe model components

Additionally to standstill detection, pause reasoning is emphasised. Therefore, three pause reasoning buttons are added to the lathe and used by the operator in the time of standstill in turning. Three buttons are named as “Planned maintenance”, “Fault” and “No order” and are available for operator to press, respectively. Planned maintenance is pressed in time of maintenance that is previously planned by maintenance mechanic and this stop is taken into account in production plan. Fault means unplanned pause that is caused by unexpected behaviour of the machine tool. It can be breakage of some machine tool components, malfunctioning of the machine tool or a sudden decrease in machining quality. No order means lack of cutting file, engineering drawing, raw material or work order. This is directly related to the lack of preparation work in office. The number of buttons could be increased to specify the pause roots deeper and in more detail in implementation in shop floor. Led indicator starts to light, if lathe standstill between working cycles has been longer than specified normal setup time. It means, for continuing, the operator has to choose one of the buttons to specify the pause reason. Led turns off if one of the buttons is pressed as long as the signal moves from the lathe model to the control PC and a confirmation signal comes back to the led.

The NI graphical programming environment LabView was used to design a virtual instrument with the GUI to detect real-time and also dataset based information. The programme defines relations and connections between components and the GUI, senses voltage threshold value and programme peculiarity (Figure 3.9).

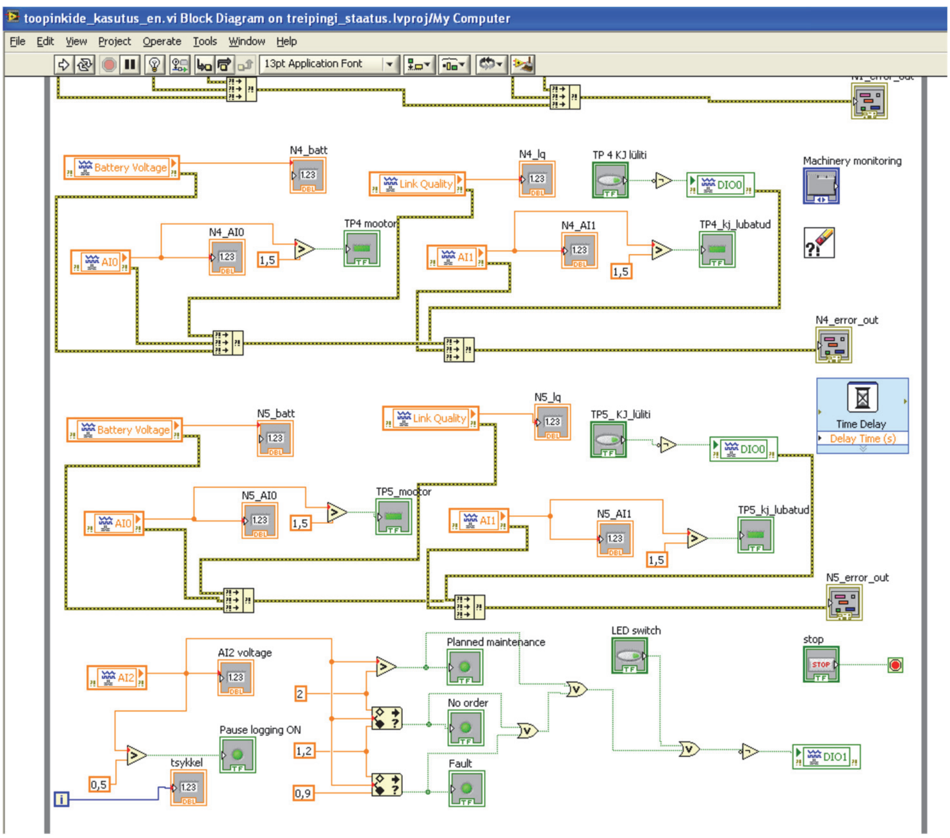

Figure 3.9. Fragment of block diagram of status monitoring program in LabView

The GUI is divided into four views. In the main view, there is an activity indicator light for every workbench and this is lit when particular lathe motor is working. Additionally, remote control status is presented and there is a remote control. The second view is for pause reasoning monitoring and standstill reasons are displayed in real-time for every lathe. The third view is for dataset-based information. The fourth view is important for maintenance as it shows error messages for debugging, battery load in voltages, and wireless communication quality in percentages.

The designed demonstration toolkit has been introduced to mechanical engineering master students, who have been positively surprised to see physically and test state-of-the-art monitoring solutions. The demonstration toolkit has also been an icebreaker between the TUT and private manufacturing companies to start new projects together.

4 RESULTS AND DISCUSSION

4.1 Results

In CNC turning, both acceleration sensor based range value analysis in time domain and acoustic sensor based frequency spectrums analysis in frequency domain show a distinguishable difference between a failure situation and a stable working mode. Graphical representation of acceleration signal shows a visual difference between stable turning and turning with failure that ended up with tool breakage. In CNC turning stable working mode and unstable working mode are also distinguishable based on accelerometer measurements and range value analysis in the time domain. According to the analysis, 130 successive measurement values with 160 Hz frequency were reported as sufficient in accelerometer-based monitoring.

In the CNC milling machine, current consumption monitoring, based on threshold values, enables to distinguish machining statuses as switched off, the main engine working, and the spindle turning. Whereas current consumption difference in spindle idle turning and in a stable cutting mode are lower than the accuracy of the measuring device.

In laser cutting, acoustic signal-based status monitoring with spectral means extraction method and with a fuzzy classification algorithm shows high reliability, 98.05%. In CNC routing accelerometer-based monitoring, two analysis methods gave the same high result 99.85%: spectral means feature extraction with correlation based classification and the MFCC feature extraction with a fuzzy classification algorithm.

In turning, multichannel acoustic signal monitoring shows that linearly placed microphone arrays give reliability 90.5% in status monitoring. Angularly placed microphone arrays give reliability 94.5%.

4.2 Discussion

Various machine tool status monitoring sensing methods with various analysis methods were experimented. Different methods have different benefits and drawbacks. Current consumption measurement-based method is easy to analyse through the threshold value. However, the drawback of this method is that the measuring device must be connected in series connection before the machine tool. It means that an ammeter must be between a plug and the machine tool, therefore electrical input for machining passes the measuring device first. It means failures in the ammeter can cause problems in machining and decrease the availability and reliability of machine tool. The benefit of acceleration sensor-based measurements is a wider usage of sensed data. The in-process vibration helps estimate also the working mode, cutting tool condition and the part surface roughness. On the other hand, the drawback is that accelerometer needs very close connection with cutting tool – workpiece contact point but it needs protection in case of cooling fluid usage in machining. Multi-channel acoustic sensors measurement based method has great potential if sensing area could be expanded to the whole shop floor. The benefit of multi-channel measurement is also a nonphysical contact with the machine tool that means easier installation.

The proposed modular design of machining processes monitoring system allows implementation and installation of monitoring modules step by step. It makes the implementation of machining processes monitoring affordable also for low budget SMEs. Furthermore, wireless sensors are easier and cheaper to install than wired solutions. After obtaining increased efficiency in productivity and increased product quality with the first monitoring module, managers are probably in favour to expand the system with new modules.

When using wireless sensors in monitoring it is important to be aware of some peculiarities.

- Wireless sensors use batteries for energy consumption. It means that nodes are not purely maintenance free. The RF is the biggest energy consumer. Energy consumption can be diminished through on-board computing and transmission of analysed data only. For instance, NI WSN nodes are powered with four AA-batteries and offer up to three-year lifetime [NI, 2014].
- Manufacturing environment decreases the broadcast area of transmission of wireless nodes. For instance, NI gateways use 2.4 GHz, IEEE 802.15.4 radio to communicate with nodes up to a 300 meters outdoor range with line of sight [NI, 2014]. In metal working industry, interference by metals causes the noise that decreases the transmission area. In this reason, special router nodes must be used to shorten the transmission distances.
- Wireless nodes sampling frequency must be in accordance with sensed data characteristics. Measuring vibrations or acoustics with sampling frequency 1 Hz does not give adequate information. According to test, 160 Hz sampling frequency in a lathe working mode detection gives optimum results. In contrast, temperature monitoring on lathe spindle bearing with sampling frequency 1 Hz is sufficient.

"Real-time" in monitoring manner means as soon as possible. Data collection, extraction, analysis, transmission and displaying – everything takes some time. For a working mode detection 0.8 seconds was found to be optimum time of vibration signal length for analysis. The time for data processing depends on a number of computational operations that are needed for achieving reliable results. Processor speed is characterised with Hz. For instance, 1 kHz processor can make 1000 computational operations per second. Transmission speed depends on nodes configuration in energy consumption point of view. If the node's RF channel is held awake all the time, data is transmitted immediately. Being awake means continuous energy consumption even in operation break times such as lunch break. Another option is to configure nodes to wake up the RF module periodically to send out data periodically (for instance once per second). Optimum relationship between energy consumption and transmission speed needs to be found for every monitoring module. Depending on previously described configurations, real-time monitoring delay is about 2 – 3 seconds.

In machine tool health monitoring, in status monitoring and in tool insert life monitoring a 2 – 3 second delay is acceptable, while failure prevention on working mode monitoring is difficult by the operator. The operator also has reaction time needed for changing / stopping a process. Incorrect working parameters can cause a failure (tool insert breakage) with few seconds. For relatively unstable working condition control, adaptive feedback is more reliable than operator. However, in working mode smoothing for quality assurance and control, the operator is essential.

For status monitoring module, different vibration, acoustics and current consumption based experiments were conducted. In some cases, spindle idle turning and stable cutting operation are hard to distinguish. But the main engine working and stable cutting mode are reliably distinguishable. Spindle idle turning situations are not productive and should be avoided in the manufacturing shop floor. Therefore, spindle idle turning and cutting status distinction is not crucial and does not affect reliability of machine tool status monitoring.

In the same way as in WSN communication, the RFID communication can also be interfered by metals. Typical label-type tags with dipole-like antennas do not work efficiently on metallic surfaces. A metallic surface changes the radiation pattern, radiation efficiency, resonant frequency, and input impedance. Microstrip-based antennas have been modified to work on metal surfaces but these are considerably more expensive to manufacture. In metal industry sometimes RFID tags are separated from metal with thin low dielectric material as flexible foam layer. A 3.2 mm thick foam layer between metal surface and the RFID tag improves the reading distance by about 85% [Mohammed *et al.,* 2009]. Additionally, the Confidex Ironside on-metal Gen2 UHF tag [Confidex, 2014] is invented for on-metal applications.

The DOMe usage in machining operations as turning has been investigated only theoretically and its machining environment usability has not been tested so far. One of the challenges in the DOMe adaptation in turning is the RFID readability in high speed turning. This can be solved with workpiece DOMe G-code related information copying and temporary storage into smart environment or cutting tool memory. The second challenge is G-code’s smooth recognition. The problem is that there are more than 5000 different dialects of the G-code. In principle, every machine tool controller – the CAM pair has a unique language. They are all called the G-code but they have slight differences and modifications. Mostly the main G and M codes are the same but there are differences in string numeration, number zero addition on front of some numbers, etc. The third challenge is the correct preservation of the RFID tag during operations and selection of the attachment area. The tag must not be attached to the surface which are worked during manufacturing processes or has to be repositionable between machining processes.

5 CONCLUSIONS

Conclusions

The general conclusions of the work are as follows.

1. A new approach for wireless real-time machining processes monitoring system development and implementation was introduced.
   - It was found that appropriate monitoring system for SMEs is modular and step by step expandable. Modularisation of the monitoring system was performed based on application modules information characteristics. The machine tool monitoring system was composed from five modules: machine tool health monitoring, status monitoring with pause reasoning, cutting process working mode detection, tool insert life monitoring and part quality monitoring with on-board data storage.
   - A value-centric approach in planning of monitoring modules enables to keep the focus on the main problem and to obtain a knowledge-based solution.
   - The developed concept of Monitoring cycles for performance improvement structures the monitoring system according to the main interested parties, determines their main responsibility in the performance improvement chain, and indicates the related relevant monitoring information. It divides the main interested parties into four groups: the mechanic, the operator, the production manager, and the top manager.
2. In status monitoring experiments, high reliability was achieved and a demonstration toolkit was constructed.
   - In laser cutting, the highest reliability 98.05% was achieved using the acoustic signal-based spectral means extraction method with fuzzy classification algorithm.
   - In CNC routing, the highest reliability 99.85% was achieved in acceleration based monitoring. Two analysis methods gave the same result: spectral means feature extraction with correlation based classification and MFCC feature extraction with fuzzy classification algorithm.
   - In CNC milling, threshold value 2 A was found to separate main engine working and spindle turning statuses.
   - A novel demonstration toolkit model for machine tools status monitoring and pause reasoning with real-time GUI was successfully used in introducing of machinery monitoring system options for private companies to start new projects and also for master course students.

3. Concept for the DOMe integration into part and machining quality automatic real-time monitoring and data storage was developed. According to the developed concept, every workpice DOMe contains its processing G-code that can be used together with smart cutting tool based in-process signal to evaluate tool condition, part surface roughness and cutting mode.

Novelty

Novel solutions as follows were proposed and presented:

- A new approach in planning and structuring for monitoring of machining processes was presented. Novelty lies in the combination of following features: modularity of monitoring system, value-centric application design, in-process machining signal evaluation, wireless data collection, gathered data personalisation, and distribution to every interested party in real-time. Furthermore, a novel structuring concept of “Monitoring cycles for performance improvement” was introduced.
- New sensing, feature extraction and analysis combinations for various machine tools status detection were experimented and analysed. For instance, laser cutting was monitored using acoustic sensor, spectral means feature extraction and fuzzy logic based class labelling method (reliability 98.05 %); the CNC router was monitored using accelerometer sensor, MFCC-based feature extraction and fuzzy logic based class labelling method (reliability 99.85 %); the CNC lathe was monitored using set of acoustic sensors, multiple feature extraction methods and fuzzy rule-based classification method (reliability 90.5 %).
- A novel WSN and LabView based status monitoring and pause reasoning demonstration toolkit with real-time GUI was developed, designed, and constructed. The demonstration toolkit is portable and easy to use in the class room and in meetings with potential project partners.
- A concept of DOMe integration into part and machining quality automatic real-time monitoring in turning. Novelty lies in DOMe usage in machining process automated quality monitoring. Evaluation of the in-process signal is executed according to the presently running G-code. The relevant data is also stored in the related DOMe and the data is available all over the becoming product further life cycle.

Further research

Development of the CPPS continues to achieve the objective, 30% overall efficiency growth in the shop floor and to announce the beginning of the fourth industrial revolution.

An intelligent manufacturing environment together with monitoring applications move towards the concepts of IoT and All IP. These concepts gather the idea that every component in the shop floor is equipped with an embedded computer, Internet protocol (IP) address and Internet connection capability. It would allow direct online monitoring, without gateways as data collectors and distributors. Additionally to explicit technical solution, it also requires crossing of psychological barrier to enable switching over Internet and communication between components. Today, most of office-related information in companies has already held in cloud and managers are probably open for similar development for shop floor-related actions.

Similar IP address-based solution is researched also in the field of electrical engineering. A concept of smart grid is introduced and developed to optimise energy consumption in constant change and volatile energy price situation. As prices of the energy stock are continuously changing, depending on the number of consumers (demand) and quantity of produced energy (supply), automatic production lines could be added to the smart grid system.

Machining processes real-time wireless monitoring needs further research in next areas.

- Connection of a smart grid with machine tool monitoring to optimise the company efficiency through diminishing the manufacturing input cost. Production lines could be run more in time of lower energy cost and maintenance served in energy cost peak times.
- Further analysis and development of in-process signal related algorithms is needed to evaluate more precisely machine tools working modes and cutting tool condition.
- Experimentation and evaluation of DOMe-based machining process monitoring with automated monitoring information storage on-board of a part.
- Further improvement of semantic context based communication between components, machine tools, products and workers in shop floor is the topic with high importance. This is the key factor to achieve seamless automated flow of processes beyond all shop floor activities.

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ACKNOWLEDGEMENTS

My biggest thanks to my supervisor Professor Tauno Otto for excellent support, instructions and guidance throughout the research.

Respectful thanks to Professor Wolfgang Maaβ for high value recommendations during my research in Saarland University.

Special thanks to Mr Risto Serg for strong support in the field of automatics. Additionally, I would like to thank the persons who cooperated for the research purposes and shared their knowledge with me, especially: Kristo Karjust PhD, Jüri Majak PhD, Jürgo-Sören Preden PhD, Mr. Aleksei Snatkin, Mr. Sergei Astapov, Mr. Igor Poljantšikov, Mr. Johannes Ehala, Mr. Taavi Reinson, Ms. Sabine Janzen, Mr. Andreas Schorr and Mr. Andreas Filler.

Great thanks do my dear family for the unconditional support during the studies and research.

ABSTRACT

Wireless Real-time Monitoring of Machining Processes

Changes in customer expectations have led to changes in the manufacturing environment. High flexibility and mass customisation are considered as main trends in the shop floor. To avoid decrease in productivity and furthermore to turn the inevitable chances to the strength, fast and trustful feedback from machine tools is needed. A tool for its realisation is real-time monitoring of the machining in-process signals.

The main objective of the research is to develop modules of wireless real-time machining processes that form a monitoring system. The purpose of the new approach is to make modules of machining processes monitoring system easily implementable and affordable for industrial manufacturing SMEs, while retaining monitoring system reliability. To obtain the purpose, the following subtasks are in focus: development of monitoring modules based on machining processes in-process signals and wireless sensors; analysis and evaluation of machine tool working mode and machine tool status monitoring experimental data; construction of machine tools status monitoring prototype toolkit with real-time GUI; working out the concept for RFID and DOMe-based tracking solution integration into parts machining performance monitoring module.

The new methodology composes a monitoring system from five independent modules: machine tool health monitoring, machine tool status monitoring with pause reasoning, cutting process working mode detection, tool insert life monitoring, and part quality monitoring with on-board data storage. The new concept of monitoring cycles for performance improvement bonds the modules into the enterprise level system and divides the modules between main interested parties according their main tasks for ensuring seamless and efficient manufacturing flow. The value-centric approach in planning and development keeps the focus in main problem and obtains knowledge-based solutions.

Research analysis and compares various machine tool status monitoring techniques. Various in-process signals as vibrations, acoustics and current are analysed in time and frequency domain. Various feature extraction methods as MFCC, spectral means, band energy, spectral centroid, spectral roll-off and spectral slope are used in combination with various classification methods, such as fuzzy rule-based classification and correlation-based classification. High reliability is achieved in laser cutting, turning, and milling. Time domain range value based analysis is performed in working mode evaluation and optimum measuring parameters detection. Additionally, a novel status monitoring prototype demo toolkit with real-time GUI is introduced.

The thesis proposes a new concept to integrate the DOMe into part and machining quality automatic real-time monitoring and data storage. Intelligent environment uses the on-board G-code with smart cutting tool based in-process signals to evaluate tool condition, part quality and cutting mode.

The new approach of machinery monitoring system gives instructions for the system reasoned implementation in SMEs. It enables to start with smaller cost that has been the main obstacle for many companies so far. Additionally, digital object memory implementation in monitoring system enables to make automated quality control and reuse the physical product-related information through the product lifecycle.

KOKKUVÕTE

Juhtmevaba reaalajas lõiketöötluse monitooring

Muutused klientide ootustes on avaldanud mõju ka protsessidele tootmiskeskkonnas. Paindlikkuse kasv ja väiksemaks muutuvad partiid on saanud peamisteks trendideks tootmistsehhis. Selleks, et need muutused ei tooks kaasa tootlikkuse langust, vaid vastupidi, tugevdaksid ettevõtte positsiooni, on hädavajalik saada kiiret ja usaldusväärset tagasisidet tootmisseadmetelt.

Töö peamine eesmärk on arendada lõikeprotsesside juhtmevabu reaalajalisi monitooringu mooduleid, mis üheskoos moodustavad monitooringu süsteemi. Uudse lähenemisviisi eesmärk on muuta lõiketöötlusprotsesside monitooringu moodulid lihtsamalt evitatavaks ja esmase investeeringu summa poolest atraktiivsemaks väikese ja keskmise suurusega tootmisettevõtetele. Kuid samal ajal säilitades monitooringu süsteemi usaldusväärsuse. Eesmärgi saavutamiseks on fookus suunatud järgmistele tegevustele: lõikeprotsessi siseste signaalide ja juhtmevabadel anduritel põhinevate monitooringu moodulite arendus, tootmisseadmete töörežiimide ja tööaja jälgimisel põhinevate eksperimentaalsete tulemuste analüüs ja hindamine, tootmisseadmete tööaja jälgimise prototüüpmudeli valmistamine koos reaalajalise graafilise kasutajaliidesega, RFIDl ja digitaalsel objektimälul põhineva jälgimislahenduse integreerimine detaili lõikeprotsessi hindamise monitooringu moodulisse.

Uudse metoodika kohaselt koosneb monitooringu süsteem viiest iseseisvast moodulist: tootmisseadmete seisundi jälgimine, tootmisseadmete tööaja jälgimine koos pausi põhjuste selgitamisega, lõikerežiimi jälgimine, lõiketera seisundi jälgimine ja detailide kvaliteedi jälgimine koos info salvestamisega detailile. Uudne lähenemisviis põhineb tulemuslikkust parendavail monitooringu tsükleil. Monitooringu tsüklid jagavad monitooringu moodulid kaasatud osapoolte vahel vastavalt iga osaleja peamisele tööülesandele ühtlase ja efektiivse tööprotsessi säilitamiseks. Väärtuskeskne lähenemine moodulite plaanimisel ja arendamisel hoiab fookuse põhiprobleemil ja võimaldab saavutada teadmuspõhist lahendust.

Töös uuritakse ja võrreldakse erinevaid tootmisseadmete tööaja jälgimise tehnoloogiaid. Erinevat tüüpi protsessisiseseid signaale nagu vibratsioon, akustika ja voolutugevus analüüsitakse nii aja- kui ka sagedusvallas. Erinevad signaali iseloomustavate tunnuste väljavalimise meetodid on kombineeritud erinevate signaalide klassifitseerimise meetoditega ja omavahel võrreldud. Selle tulemusel on kõrge usaldusväärsusega tulemused saavutatud treimisel, laserlõikusel ja freesimisel. Töörežiimide hindamine ja optimaalsete mõõteparameetrite välja selgitamine on läbi viidud ajavallas kasutades peamiselt signaalide haaret. Lisaks sellele tutvustatakse uudset tootmisseadmete tööaja jälgimise ja pausi põhjuste tuvastamise prototüüpi, mis jagab reaalajalist infot graafilise kasutajaliidese vahendusel.

Töös pakutakse välja uudne kontseptsioon digitaalse objektimälu integreerimiseks detaili ja selle lõiketöötluse automaatseks reaalajaliseks monitooringuks ja saadud andmete salvestamiseks. Tooriku mälus oleva G-koodi ja targa tööriista poolt mõõdetavad lõikeprotsessi sisesed signaalid seotakse omavahel intelligentse keskkonna vahendusel, et automaatselt hinnata tööriista olekut, detailide kvaliteeti ja lõikerežiimi ning salvestada saadud informatsioon tootele.

Välja töötatud uudne lähenemine lõiketöötluse monitooringu süsteemile annab juhiseid selle läbimõeldud evitamiseks väike- ja keskmise suurusega ettevõtetes. See võimaldab alustada monitoorimist väiksemate algkulutustega, mis on siiani olnud paljudele ettevõtetele peamiseks takistuseks. Lisaks võimaldab objektimälu kasutusele võtmine lõiketöötluse monitooringus pakkuda automaatset kvaliteedikontrolli, mis seotakse füüsilise tootega kogu selle elutsükliks.

APPENDICES

PAPER I

Aruväli, T.; Serg, R.; Preden, J.; Otto T. (2011). In-process determining of the working mode in CNC turning. *Estonian Journal of Engineering*, 17(1), 4–16.

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

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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

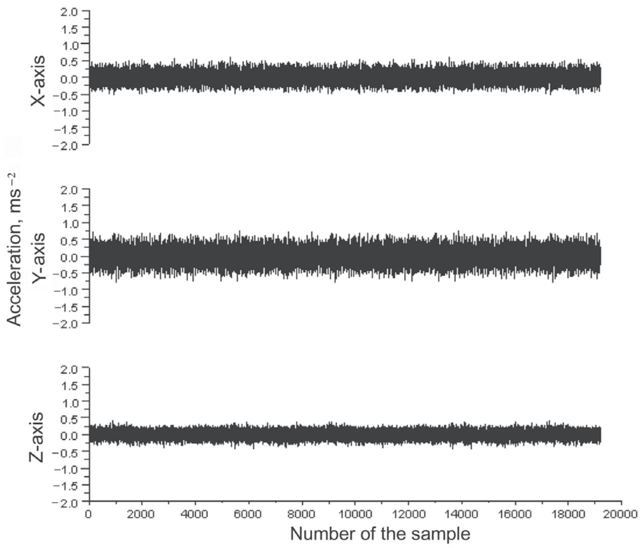

Fig. 1. Noise floor level test No. 1.

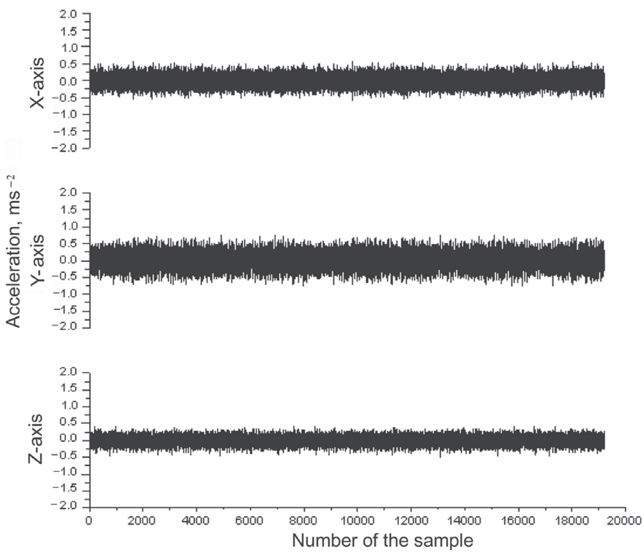

Fig. 2. Noise floor level test No. 2.

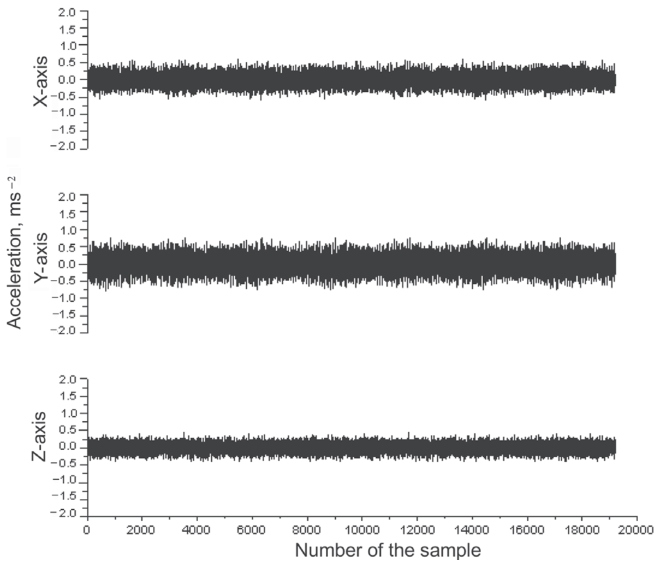

Fig. 3. Normal working mode test.

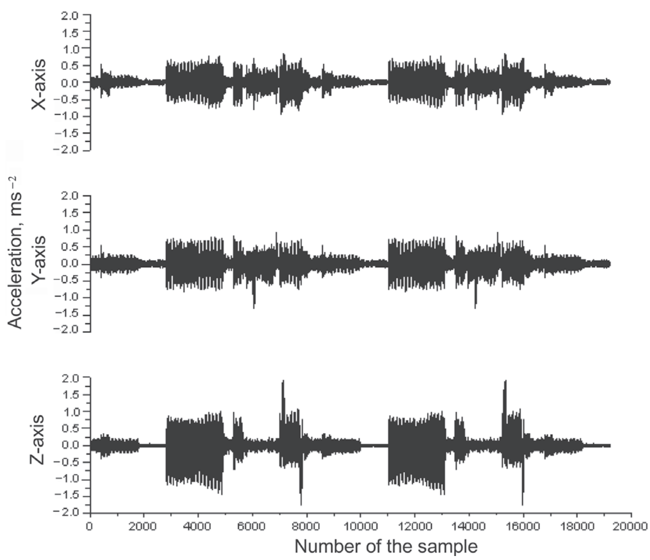

Fig. 4. Fault situation test in high speed.

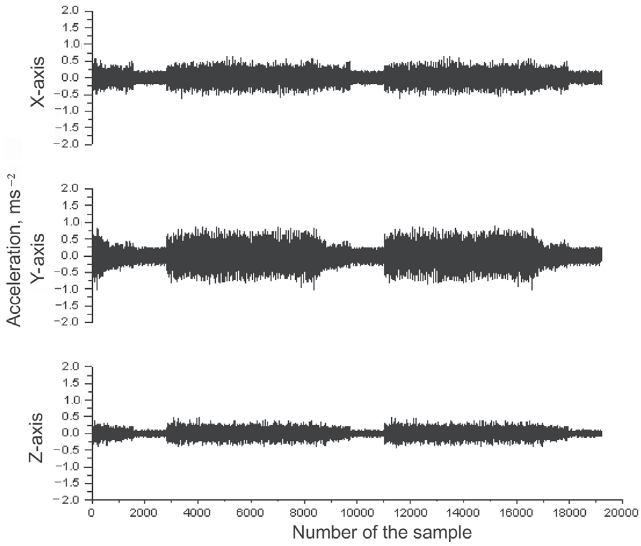

Fig. 5. Fault situation test in normal speed.

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.

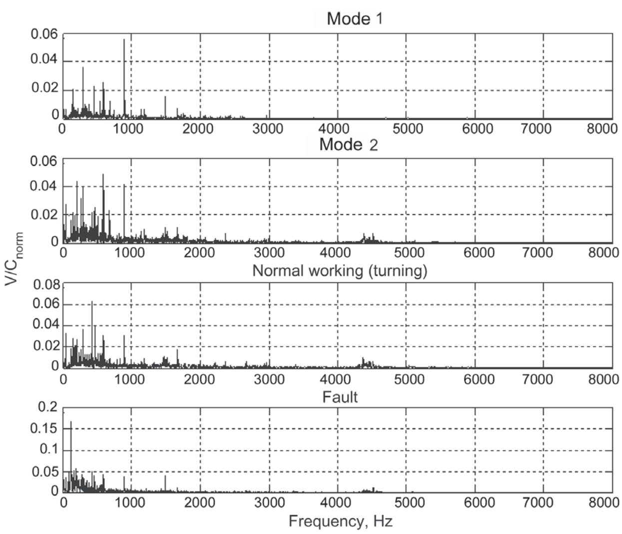

Fig. 6. Modes 1–4 in turning.

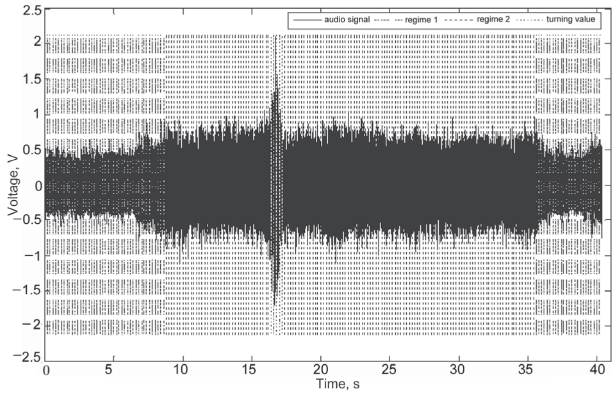

Fig. 7. Acoustic signals in different modes.

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).

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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 keskssesse 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.

PAPER II

Aruväli, T.; Reinson, T.; Serg, R. (2011). Real-time machinery monitoring applications in shop floor. *Proceedings of the World Congress on Engineering and Computer Science*, 337–342.

Real-time Machinery Monitoring Applications in Shop Floor

Tanel Aruvali, Taavi Reinson, Risto Serg

Abstract—**Monitoring in shop floor is of great importance to achieve better quality and save the environment. Embedded computers are used in wireless sensor network (WSN) monitoring systems to process data and provide quick feedback. A method for detecting working modes based on vibrations in CNC lathe is introduced. Optimization of nodes energy usage has also been taken into account as an essential parameter in WSN. In addition, a sample WSN production monitoring system was positively tested and suggestions for raising its accuracy were proposed.**

Index Terms—**Production environment monitoring, tool wear, vibration, WSN nodes**

I. Introduction

MANAGING operators and controlling a work of machineries are of great importance in shop floor. For managing efficiently machinery operators, feedback from working process is needed. For controlling and operating machinery efficiently, feedback concerning machinery, tools and working piece is essential.

Classical feedback methods like visual estimation, machinery noise comparison and collection of information touching work piece are not reliable and measurable. In modern and competitive manufacturing company machinery monitoring system should be utilized to achieve the highest quality, to reduce perversion of material and to prevent damages of machinery and tool failures. The last two damages are especially harmful for production, causing unplanned breaks in production and delays in fulfilling customer orders.

In modern factory it is essential to employ wireless sensors for monitoring. Wireless measurement and monitoring systems provide an opportunity to reduce installation and system costs, increase flexibility, simplify system deployments, and address a new set of applications that were previously challenging or impossible with a wired approach. 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 existing process. The installation cost of cable in industrial plant can vary greatly based on the type of plant and physical configurations. According to studies the average cable installation cost lies between 10 $ and 100 $ per foot [1], in nuclear plants as high as 2000 $ per foot.

Turning operation is a common metal working process in modern manufacturing industry. Due to its wide utilization, many researchers have analyzed this process in detail. The main research areas have been influenced by cutting forces [2], vibrations [3], temperature [4], acoustic [5], chip formation [6], and tool wear [7] in accordance with improving surface roughness. The main goals of these researches have been to achieve better work piece surface quality by changing cutting parameters as feed rate, cutting speed, and depth of cut and work piece material.

Optimum cutting parameters help to improve cutting quality, but they are not always applied. It is often complicated to use them, since they are floating parameters depending on the level of tool wear. Considering this, it can be concluded that being aware of optimum parameters does not ensure their usage. Consequently, the most suitable working mode is not always applied.

Besides using optimum cutting parameters it is important to change tool insert on time to maintain the cutting quality. Every tool insert has a limited lifespan. In case the time outlasts, a turning result is poor, irrespective of cutting parameters.

Every tool has an average lifespan in minutes, but depending on the way of usage, it may vary considerably. In order to avoid poor quality in turning it is not sufficient to count working minutes. It does not always provide a reliable result according to working mode used. Also visual detection of tool wear level is inaccurate and may depend on operator. For tool wear level identification there is a great need for automatic indicator.

It has been found that tool lifespan is in correlation with the amount of vibrations [8]. Vibration also signals differently in a fault situation [9]. Deeper investigation of vibrations gives the possibility to predict the tool lifespan.

Smart tool is a target for many researches. Sensor fusion system is utilized for monitoring tool wear level in turning. Fusion system includes a force sensor, a sound sensor, an accelerometer sensor and an acoustic emission sensor [10, 11].

The aim of the article is to analyze WSN network tool kit to estimate its stability and reliability in production environment. Additionally, turning machinery working modes have been investigated in vibration section to create a

Manuscript received July 8, 2011; revised August 19, 2011. This research was supported by the competence centre IMECC, Estonian Ministry of Education, Research Project SF0140113Bs08, Estonian Science Foundation (grant F7852) and European Social Fund’s Doctoral Studies and Internationalisation Programme DoRa. Author´s thanks also company Densel Baltic for using their CNC machinery.

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smart turning tool that can indicate its wear level.

II. Sample WSN Production Environment Monitoring System Test

Measurement method

Real time monitoring system has to be wireless to enable easy installation and quick adjustment for utilization.

A sample tool kit system for production environment monitoring was created. Sensor system bases on Wireless Sensor Network (WSN) technology produced by National Instruments. The sample system consists of three WSN nodes, one gateway, a user interface with processor (touch-screen computer with environment analyzing program in LabViw environment) and three sensors for measuring temperature, relative humidity and force (Fig. 1). This monitoring system was created in order to test stability and reliability of WSN nodes in production environment and to evaluate nodes compatibility with different type of sensors.

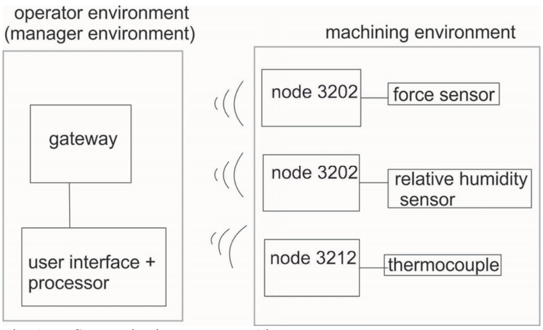

Fig. 1. WSN monitoring system architecture

Gateway is a device that creates Ethernet type wireless network between nodes and computer. It uses a standard IEEE 802.15.4.

All the sensors attached to the nodes were powered using the node's internal sensor power output terminal SEN PWR. The correct supply voltage of the sensors was secured by voltage regulator connected between the power terminal of the node and the input terminal of the sensor. The supply voltage of the sensors varied between 5 V to 10 V. All sensors used within the system had a voltage output which the nodes were able to measure. The output signals of the sensors were calculated into their expected shapes using formulas provided by sensor producers.

In sample monitoring device, total duration of measurement and cycle length has to be entered to start monitoring. As a result, user interface software displays all the measured values on the screen both numerically and graphically. All the results are also saved in log files. This method allows the measurement data to be analyzed later in more detail if necessary. The software of this measurement system contains also an analyzing tool which enables the user to get a quick overview of measurement results.

The measured parameters were chosen based on the capability of the nodes. The maximum cycle rate at which WSN-3202 node can measure voltage is 10 Hz. Since this cycle rate is rather slow, it limits the choice of parameters measurable by the nodes. Therefore, parameters used in the system fluctuate at low frequencies.

The test contained measurements of temperature, force and relative humidity. Measurement of temperature was one part of achieving the result of relative humidity.

All the measurements taken with nodes were compared with a reference result measured at the same time with a device of higher accuracy. This comparison provided a sufficient overview about the accuracy of the developed WSN monitoring system. All the measurements were taken simultaneously with the reference device in order to get a direct comparison between different nodes.

Measurement process of relative humidity

Relative humidity test was performed in a CTS C40/1000 climate chamber. All the measured values were compared with a reference result taken with Hygroclip HC-2SH humidity and temperature measurement probe. The accuracy of the reference probe is ±0.01 °C and ±0.5% RH, which exceeds the accuracy of nodes by several times.

The test was performed using a WSN-3202 node and a humidity sensor produced by Honeywell. All the relative humidity measurements were taken at 20 °C. During relative humidity tests, measurements of temperature were simultaneously utilized. The output signal of relative humidity sensor is affected by the temperature of the measuring environment. WSN-3212 node with J-type thermocouple was utilized for temperature measurement. The relative humidity levels used for the test were 20%RH, 40%RH, 60%RH, 80%RH and 90%RH.

Relative humidity was measured with sensor of Honeywell HIH-4000-003, with accuracy ±3.5% RH. As the supply voltage was 5 V and output voltage was 12 V, a voltage regulator had to be connected before the sensor. For holding stability of supply voltage also two capacitors (3.33 μF and 0.1 μF) were connected. Output voltage of sensor was measured between terminals SEN OUT and GND. Terminal GND was used for grounding the supply voltage. MC7805 is a voltage regulator. The circuit diagram is presented in Fig 2.

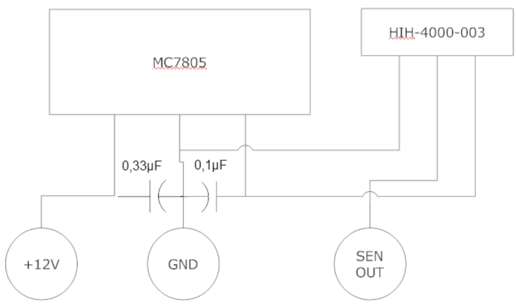

Fig. 2. The circuit diagram of measurement of relative humidity.

A program was created in LabVIEW programming environment to measure the voltage input of WSN-3202 node and relative humidity is calculated by the use of voltage. Sensor 0-point has been taken off from the voltage and the result is divided with the sensitivity of the sensor. As a result, the relative humidity sensor is subject to temperature, also temperature coefficient has been taken off.

After the first test the sensitivity of the sensor output was recalculated according to test results.

Measurement process of force

Force of the unit was measured using WSN-3202 node and Honeywell force measuring sensor FSG15N1A. Specification of the sensor is presented in Table I. Results were compared with calibrated weights.

TABLE I
HONEYWELL FORCE SENSOR FSG15N1A SPECIFICATION

supply voltage	measurement range	accuracy	consumption of current	output voltage
10 V	1500 gram	±1 gram	1.5 mA	0-360 mV

The sensor sensing element is piezoelectric resistor that changes its nominal value subject to force affected. The sensor output voltage is linearly subject to force. Sensitivity of the sensor output is 0.24 mV for 1 gram when measured at room temperature.

After the first test the sensitivity of the sensor output was recalculated subject to test results.

Results and discussion

Relative humidity test demonstrated stable accuracy in WSN monitoring system up to 60% RH. On higher level it loses its linearity and inaccuracy grows (Fig. 3). It means that the sensor accuracy ±3.5 was exceeded.

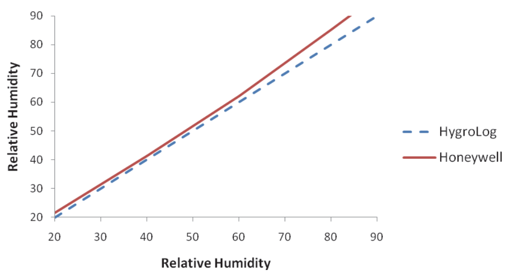

Fig. 3. Comparison of relative humidity measured using WSN monitoring system with Honeywell sensor and Hygroclip HC-2SH probe.

After analyzing the test results it was obvious that the majority of varied results were caused by sensor rather than nodes. To ensure the reliability of the monitoring system, voltage and humidity ratio constant was changed. The new constant was midrange of signal/expected value ratio. Original constant 0.031 was changed to 0.0328 and a new test was utilized with the new constant. After constant change the results were within accuracy limits. Relative humidity test results are presented in Table II.

TABLE II
THE RESULTS OF RELATIVE HUMIDITY TEST

expected value (%RH)	node value (RH%)	signal (mV)	signal/ expected value ratio	new expected value (%RH)	new node value (%RH)	signal noise
20	21.5	0.6665	0.033325	20.3	20.6	15
40	41.4	1.2834	0.032085	39.1	38.9	20
50	51.8	1.6058	0.032116	48.9	49.2	21
60	62.1	1.9251	0.032085	58.7	58.5	23
80	85.3	2.6443	0.033054	80.6	80.6	26
90	97.4	3.0194	0.033549	92.0	91.8	30

Force measurements difference between measuring instruments outputs was maximum 10% in low values, in higher levels about 7%. WSN force monitoring system exceeded its accuracy limits ±1 gram. Maximum difference was 14.9 grams at the highest force level (Table III).

Similarly to humidity test, output value calculation constant was changed. New constant was midrange of signal/expected value ratio. New constant 0.259 increased the reliability of measurements. Force sensor accuracy comparison at different load level is presented in Fig. 4.

It can be concluded that all nodes used in the tests performed as expected. The performance of the nodes was stable and all the nodes acted equally in comparison with each other. It can also be concluded that when using external sensors, the accuracy of measurements depends mostly on the accuracy of the sensor rather than the accuracy of the node. Before using nodes with sensors it is strongly recommended to compare the results with instruments of higher accuracy. Based on test results adjustment of output value calculation constants has to be carried out to achieve the highest accuracy.

TABLE III
THE RESULTS OF FORCE TEST

expected value (gram)	node value (gram)	signal (mV)	signal/load (mV)
0	0	0	
5	5.5	1.32	0.264
10	11	2.64	0.264
20	21.5	5.16	0.258
50	53	12.72	0.2544
100	106.7	25.608	0.25608
200	214.9	51.576	0.25788

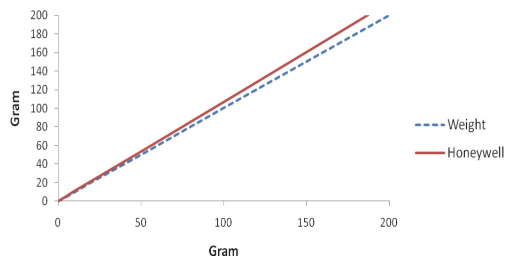

Fig. 4. Force measurement WSN monitoring system accuracy comparison using calibrated weights

WSN monitoring system is a practical tool in production environment helping to collect information for better machining results.

III. VIBRATION TESTS ON CNC LATHE

Measurement method

Vibration of the unit was measured with a solid-state micro electromechanical system (MEMS) accelerometer LIS3LV02DQ. This device can measure acceleration in three directions in the range of ±2g at 12 bit resolution. The Earth gravity was included in measurement values. This sensor type was selected as it has a suitable measurement range and accuracy, small footprint (7×7×2 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 possesses a 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 can read sensor data, buffer it and forward to the computer in serial (RS232) format.

Measurements were carried out in all 3 axes. Sampling frequency was changed during the tests from 160-2560 samples/s. For keeping WSN battery lifespan as long as possible it is recommended to take as few samples as possible. On the other hand, the number of samples has to be sufficient for analysis and decision making.

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 measurement information continuously or just monitor the identified state of machinery.

Measurement process

All measurements were carried out on a CNC turning machine Okuma OSP 2200. The acceleration sensor was bolted to aluminum L-profile and fastened with cutting tool to CNC lathe magazine and 7 sets of data acquisition experiments were conducted. Accelerometer also measures gravity of Earth and its influence is unequal in all 3 axes. Sensor output values are in units 10-3 m/s^2. These units are not changed, since every calculation uses limited energy when applying WSN as proposed.

All 7 test pieces were of the same shape and diameter 224 mm. Steel S335 was used as test piece material. New tool insert was used in test no 1. All tests were carried out with the same tool insert. Mitsubishi tool insert UE 6020 recommended linear velocity 150-250 m/min. Coolant was not used during the turning.

During the tests 3 parameters were changed (sampling frequency, feed and spindle speed that also changed linear velocity). Cut of depth was held 2 mm during the tests. Tests 1-3 were all measured in normal turning mode, thus keeping the tool insert lifespan at maximum. Linear velocity was 155 m/min which is close to lower velocity limit. The only difference between these was sampling frequency measured by accelerometer. Tests 4-6 were measured in hard working mode. Linear velocity was 380 m/min and the feed was raised to 0.4 mm/rev. Again, the only difference was sampling frequency rate. Test number 7 was carried out with empty spindle turning to recognize turning without tool usage (Table IV).

TABLE IV
CUTTING PARAMETERS IN VIBRATION TESTS

TEST NO	SPINDLE SPEED (MIN^{-1})	FEED (MM/REV)	DEPTH OF CUT (MM)	LINEAR VELOCITY (M/MIN)	SAMPLING FREQUENCY (SAMPLES/S)
1	220	0.25	2	155	160
2	220	0.25	2	155	640
3	220	0.25	2	155	2560
4	540	0.4	2	380	160
5	540	0.4	2	380	640
6	540	0.4	2	380	2560
7	540	-	-	-	640

Analysis of the results

Before carrying out the tests 4 problems were raised:

1. Is it possible to recognize normal working mode, hard working mode and turning without working based on acceleration results?
2. Which sampling frequency gives an optimum result?
3. How many successive samples are needed for analysis on optimum sampling frequency level to define the working mode running?
4. Which axis gives the best results?

Maximum range value of every test was found in all 3 axes (Table V). Comparison of range values indicates that only results measured by the same sampling frequency are comparable. Comparison can be carried out only between tests 1 and 4; 2, 5 and 7; 3 and 6. Investigating sampling frequency 640 samples/s, it can be stated that vibration level is minimum in idle running, higher in normal working mode and the highest in hard working mode. These range values are presented in Table VI in percentage. Every axis has been examined separately. The biggest difference between turning modes is in x-axis, next z-axis and the smallest in y-axis, Difference is sufficient in every axis to determine a working mode based on range values.

TABLE V
ACCELERATION RANGE VALUES ALONG DIFFERENT AXIS DURING THE MEASURING PERIOD

test no	x-axis	y-axis	z-axis
1	40	22	44
2	379	130	223
3	1397	2335	1045
4	152	290	97
5	594	394	442
6	2199	3507	1839
7	59	82	75

TABLE VI
ACCELERATION RANGE VALUES IN PERCENTAGE ALONG DIFFERENT AXIS DURING THE MEASURING PERIOD

working mode	test no	x-axis	y-axis	z-axis
idle	7	100%	100%	100%
normal	2	642%	159%	297%
hard	5	1007%	480%	589%

According to comparison of vibration graphics of different axis, x- and z-axis graphics are symmetrical, whereas y-axis is asymmetrical (Fig. 5). Y-axis has many especially high values in one direction that can distort the

ISBN: 978-988-18210-9-6
ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)

result when analyzing smaller sections. Based on this notice, y-axis is eliminated from further analysis.

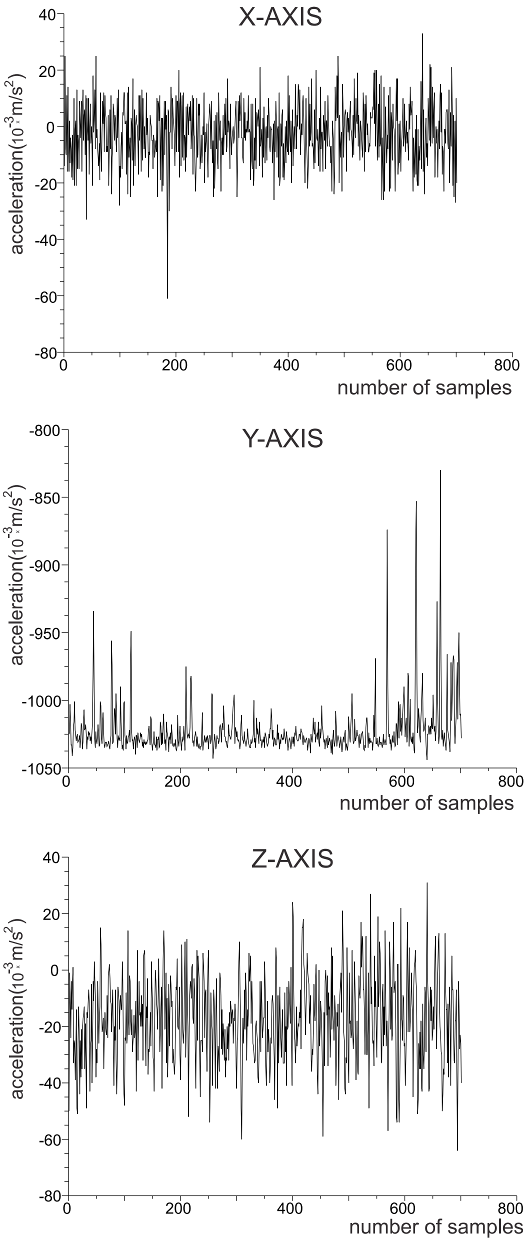

Fig. 5. Comparison of symmetry and existence of especially high values between different axes in test no 4.

Next, z-axis values have been investigated in test 1 and 2 by taking 10 random sections from every test in x- and z-axis. All sections contain consecutive measurement values. Quantity of measurement values (q) has been changed in sections to find the optimal sampling size. Range value of every section (R), as well as arithmetic mean value of these range values (X(R)) have been found. Minimum and maximum number in ranges and range value of range values (R(R)) in samplings (Table VII) have been elaborated.

For selecting the optimum section size and comparable axis the following criteria have to be considered:

1. Arithmetic mean value must be higher than the average of mean values.
2. R_{max} has to be at least 90% of whole test range value in particular axis.
3. Sections range value (R(R1-R10)) has to be lower than the average of sections range values.

The first and third points keep the values compact and limit their divergence. The second point guarantees that the calculated range stays close to the working mode in whole range value.

TABLE VII
TEST 1 X- AND Z-AXIS AND TEST 2 Z-AXIS SECTIONS COMPARISON ON THE BASIS OF NUMBER OF VALUES IN SECTIONS AND THEIR RANGE VALUES

test no	axis	q	X(R1-R10)	R_{min}-R_{max}	R(R1-R10)
2	z	130	136	104-193	89
2	z	260	152.4	111-193	82
2	z	520	167.5	128-193	65
2	z	640	171.7	135-201	66
1	z	60	25.6	19-31	12
1	z	100	31.5	21-39	18
1	z	130	31.9	28-39	11
1	z	160	31.4	27-39	12
1	x	60	29.6	24-34	10
1	x	100	31.2	27.38	11
1	x	130	32.6	27-40	13
1	x	160	32.5	30-40	10

Test 1 range was 44 and test 2 range was 223. All suitable cells in table VII have been marked with grey background. In test 2 (z-axis), using sampling rate 640 samples all compared parameters were accepted for analysis. In test 1 (z-axis) sampling rate, 130 samples meet all the requirements. In test 2 sampling rate, 640 samples fit within 1 second, in test 1, 130 samples fit within 0.8 seconds. The number of seconds indicates the time of delay in monitoring. According to previous comparison sample frequency 160 samples/s are preferred as measured in test 1. Since test 2 (sample frequency 640 samples/s) parameters were weaker, test 3 with highest sample frequency were discarded without comparison.

Finally, x- and z-axis were compared to choose the most reliable axis. The whole test range value in x-axis was 40 and in z-axis 44. All suitable cells in Table VII are marked with grey background. In x-axis the suitable sample rate was 160 samples. Above the mentioned z-axis 130 samples are also suitable and even better for collecting information in less time and using less WSN node power for wireless connection and processing the data.

Conclusions and discussion

1. Based on information of vibrations it is possible to recognize idle operation, normal working mode and hard working mode in CNC lathe.
2. The lowest sampling frequency possible in used accelerometer (160 samples/s) is fast enough for collecting reliable information to determine working

ISBN: 978-988-18210-9-6
ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)

modes in real-time monitoring. Low frequency also prolongs the time of battery life in WSN mode.

3. Section of 130 samples is optimum for determining the running working mode. It takes about 0.8 seconds to get feedback from monitoring device.
4. According to the tests, z-axis provides the most reliable result. But using different cutting parameters, also z-axis can be useful for monitoring.

IV. WSN/ Smart Dust Applications in Monitoring

The vibration tests described in the paper were performed using wired sensors. For real applications in the manufacturing floor it is essential to employ wireless sensors integrated in an e-manufacturing system [12]. Wireless sensors or smart dust motes can be used in monitoring applications in addition to the wide range of other smart dust potential applications [13]. Smart dust motes can be equipped with a wide range of sensors, thus, depending on the application the properties of a smart dust mote can vary substantially as the processing unit of the mote may also be different, to be able to process the data collected by the sensors.

So far the manufacturing reports are generally created through manual triggering by the user. However, especially for standard reports, the option of using automatic, timed report creation should be preferred. The proactive distribution of important information through the manufacturing execution system is especially useful in mobile end devices [14]. Motes can be included in this report chain, as proved in the current research.

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

V. Conclusion

WSN production monitoring device testing proved it necessary to test the accuracy of the system before utilization. Modification of constants given by producers of sensors and nodes can provide a more accurate result in production environment.

Based on vibration tests on CNC lathe, different working modes can be defined. Optimal sampling frequency of 160 samples/s and optimal number of samples for data analysis were found.

Vibration tests were carried out with cabled sensor, nevertheless, the idea of smart network and intelligent tool requires wireless connection.

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PAPER III

Aruväli, T.; Serg, R.; Otto T. (2012). Machinery utilization monitoring and pause identification prototype model design. *Proceedings of the 8th International Conference on DAAAM Baltic "Industrial Engineering"*, 256–261.

8th International DAAAM Baltic Conference
"INDUSTRIAL ENGINEERING -
19-21 April 2012, Tallinn, Estonia

MACHINERY UTILIZATION MONITORING AND PAUSE IDENTIFICATION PROTOTYPE MODEL DESIGN

Aruväli, T.; Serg, R. & Otto, T.

Abstract: *Pauses in manufacturing machinery work cause loss in factory efficiency and productivity. Detection of machinery utilization and pauses identification can give additional information for production planning and increase manufacturing efficiency. Information about machinery utilization can be processed offline to analyse past situations, but it can be also used for real time decisions. Using wireless sensors and Labview programming environment, prototype for machinery status and pauses identification was designed and introduced. Based on the prototype, proposals for industrial machinery utilization monitoring have been given.*
Key words: wireless sensor network, production planning, real time feedback, condition monitoring, machinery utilization analysis.

1. INTRODUCTION

Manufacturing enterprises main component for success is efficiency in work flow that creates the bases for high productivity. Machinery high level power and speed capability is only one indicator of workstation productivity. The other and even more important indicator is a human activity and knowledge in arranging, planning and running a workstation.

Production systems have been changed over the time and every system has its typical requirements for the machinery and production environment. In the early twentieth century Henry Ford introduced mass production that was dominating as main production system over half of century. It was inflexible, as all the produced items were similar, batch sizes were huge and items were produced to stock. Setup of production line could take months and even years [1]. But now, in modern manufacturing system, flexibility is needed. Key words of modern manufacturing systems are small batch size, flexibility, shortened production cycles, reduced work-in-progress, make-to-order and almost instantaneous delivery [2].

Thus, fast and informative feedback is needed from shop floor to fulfil modern manufacturing system requirements. Need for technology based real time wireless sensor network (WSN) monitoring system, employed by embedded computers, is getting more critical than ever before.

Machinery monitoring is in wide range researched in last years. Working modes are studied by implementing acoustic and vibration signal analysis on lathe [3]. On lathe also bearing condition is monitored using vibration signals [4]. Not only lathe, but also end-milling [5] and drilling [6] are monitored.

Even Smart Machine program has been introduced as manufacturing control system that helps in process planning, tool condition monitoring and health and maintenance [7].

Real time monitoring has multiple usages in different levels. It gives certainty to managing director, tools for better planning for production manager and fast feedback for machining quality to operator.

Modern monitoring is wireless that enables faster and cheaper installation and more flexible usage [8].

Essential is to collect the data from all the workbenches to one database to make it cognitive and simple to use. Modern machines often have database for utilization information preinstalled, but holding the information in separate machines does not give the centralised overview and contribution for productivity rise is poor.

National Instrument (NI) nodes, gateway and Labview programming environment are tools for designing wireless sensor network for monitoring. These tools have also been used in master´s study program for teaching sample real time condition monitoring system [9] and in development of broaching process monitoring system [10].

This paper introduces machinery monitoring importance and set up structure. Furthermore, it describes the design of sample NI and Labview based utilization monitoring model set up and its benefits.

2. MONITORING STRUCTURE

Machinery monitoring is beneficial for both: machineries and human competence. Efficiency in production depends on workstations productivity. Productivity is concerned as the effective and efficient utilization of resources (inputs) in producing goods (output) [11]. Preconditions for productivity are technological capabilities and human competences. Machinery monitoring can develop both preconditions (fig. 1). It helps to maintenance machines in optimised schedule, avoid inappropriate machining modes and change tools at right time. In the same time it gives information for better production and human resources planning.

Monitoring is part of modern performance improvement cycle (fig. 2). It is cooperation between operator and manager. Manager analysis results and operator comments and makes improvement decisions that are implemented by operator.

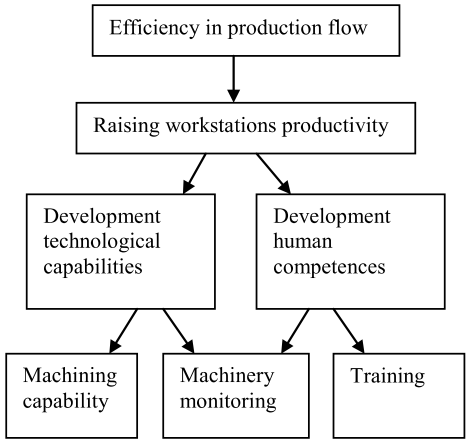

Fig. 1. Efficiency tree in production flow

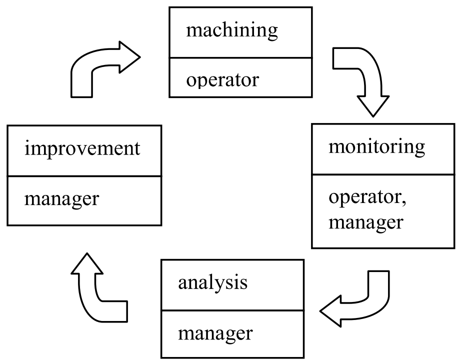

Fig. 2. Monitoring cycle

Monitoring system set up is complicated process with multiple activities that require different engineering knowledge. It requires interdisciplinary cooperation between mechanical engineers (ME), automation engineers (Aut) and information technology engineers (IT). For every activity many decisions have to be done first to develop energy efficient, user friendly and accurate system (fig. 3).

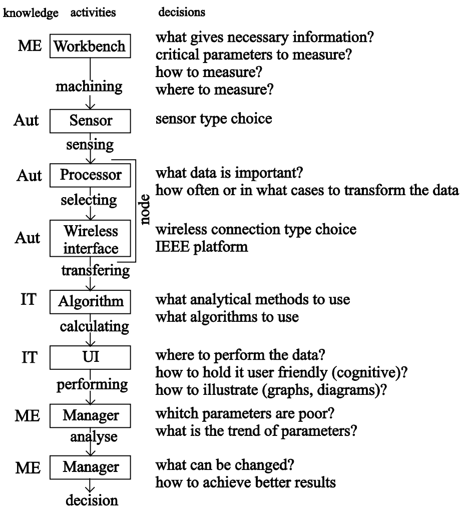

Fig. 3. Main activities and interdisciplinary knowledge in monitoring structure

3. UTILIZATION MONITORING AND PAUSE IDENTIFICATION

3.1 Monitoring importance

Utilization rate of machine tools indicates the rate of useful, productive time of machine tools compared with overall working time (workload). In one shift work, utilization rate of machine tools between 75-85% is considered effective [12].

Average small or medium size enterprise (SME) does not have exact and organised overview about utilization rate, setup times, lead time, failure rate and other unplanned pauses. The important is not only utilization rate, but also pause investigation. Pauses in machining can be caused in several reasons as jig setup, work piece setup, planned maintenance, failure in machining, preparation of CAM program, coffee breaks, missing drawing or work order and other operator based reasons.

Investigation of pause reasons helps to find out shortcomings in production planning and in work orders. Awareness of reasons enables to take knowledge based and planned steps for smoother and more efficient production.

Machinery utilization analysis helps to diminish disharmony between same type of workbenches by balancing the usage of them. Furthermore, it helps to plan resources for new orders. Utilization monitoring with pause identification gives multiple information for analysis (fig. 4).

Information displayed (monitoring)
- ↳ Questions (analysis)
  - ↳ Action (improvement)

1. At what time period workbench is utilized
   - ↳ Do we have resources for more orders?
     - ↳ Sales office regulation
   - ↳ Are we working extra hours?
     - ↳ Changing the number of shifts
2. What is utilization rate
   - ↳ What is productivity level?
     - ↳ Designing better jigs
   - ↳ Comparison of productivity between operators
     - ↳ Operators training
3. What are rate of setup time, idle time, lead time and time of failures
   - ↳ Analysis of operator work organisation
     - ↳ Rising/diminishing operator extra tasks
   - ↳ Analysis of workbench condition (failures rate)
     - ↳ Planning maintenance
   - ↳ Analysis of production management organisation
     - ↳ Improving of production drawings, work orders flow and material availability
   - ↳ Analysis of production system efficiency
     - ↳ Reorganising production system

Fig. 4. Utilization monitoring and pause identification analysis with improvement decisions

Machinery utilization analysis gives efficiency in company level. But it can be applied also in supply chain and cluster level. Giving out production information from a company expects high level trust of network organisations.

3.2 Sample prototype model design

Shop floor machinery utilization monitoring sample model was designed and programmed for presenting machinery utilization monitoring for students and production managers. Goal of the sample model is to teach effectively monitoring opportunities for students and to introduce benefits of monitoring system to production managers to popularise its usage.

To achieve all the goals, sample model has to be simple and easy to follow. It has to present utilization and pausing information in cognitive user interface (UI). Furthermore, design of workbenches has to create the feeling of shop floor to be more realistic.

Sample monitoring model kit includes 3 lathe models with micro motor and WSN node, gateway and processor with UI screen (fig. 5). Lathe model was chosen as the most typical workbench for mechanical engineer.

Models had to have the shape and properties similar with a real lathe to carry along the feeling of real shop floor. In the same time their design and electrical wiring must be visible for students. Based on these requirements PMMA sheet plastic was chosen as models structure material. PMMA is easy to process and light weight material, moreover different colours can be used. Front and back sides were created from black PMMA to carry along the feeling of always a little oily machinery. Top, right and left sides were created from clear PMMA to show wiring inside the lathe. Base was open for more curious students and for possible later improvements.

Lathe model body consists WSN node, micro motor, batteries for micro motor, switch for lathe control, relay and wiring between components.

NI graphical programming environment LabWiev was used to create the program for monitoring, to design UI for presenting utilization information in real time and also in historical view.

Graphical program as virtual instrument (fig. 6) has been built to collect the utilization information from lathe models. Real time information about state of all lathes is presented graphically in user interface main view (fig. 7). There is an activity indicator light for every workbench and this is lit when motor is working. As the monitoring system has two direction communication, additionally, remote control switch was added to the lathe to enable remote control of motor. In UI the second indicator was added to show if the workbench has remote control enabled. When remote control is enabled, lathe motor can be turned on and off from the remote computer in office or in more advanced system over the Internet.

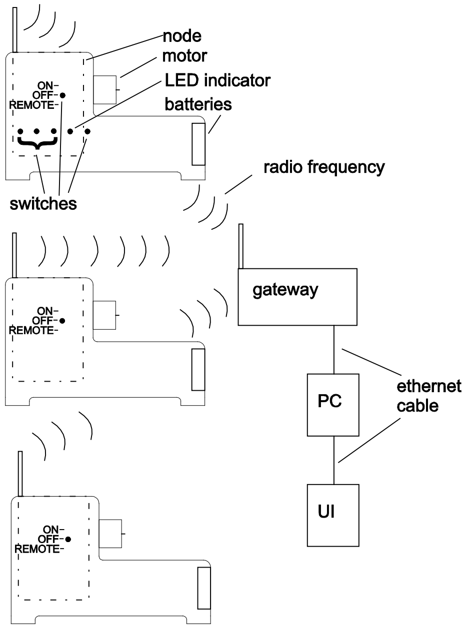

Fig. 5. Monitoring model kit structure

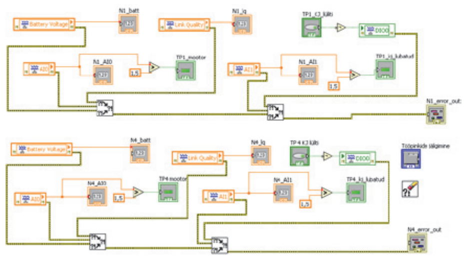

Fig. 6. Virtual instrument graphical program in Labview for lathes 1 and 4.

One of the lathe was equipped with 3 extra switches to determine the reason of pause in lathe working. Switches were named “Planned maintenance”, Fault” and “No order” that should be switched by operator correspondingly if the pause is caused by planned maintenance, fault in machining/ unplanned maintenance or operator is lack of work order, drawing or material. The reason of pause is indicated in UI panel (Fig. 8) and saved to the database.

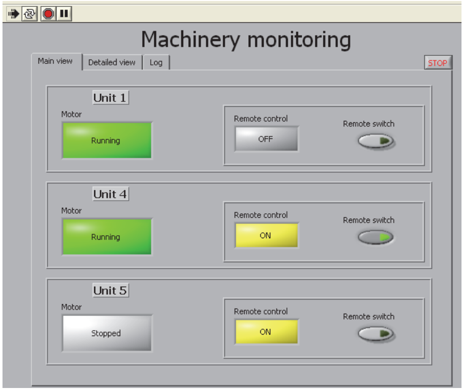

Fig. 7. UI, main view: workbenches utilization and remote control information

UI page 3 has detailed view of battery energy and radio frequency quality information (Fig. 9). UI page 4 has historical view graphical presentation of lathe utilization and pausing information (Fig. 10).

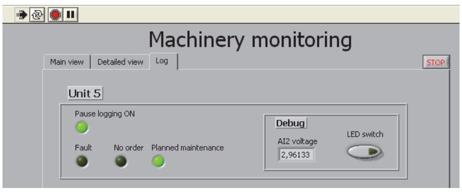

Fig. 8. UI, Investigation of pauses

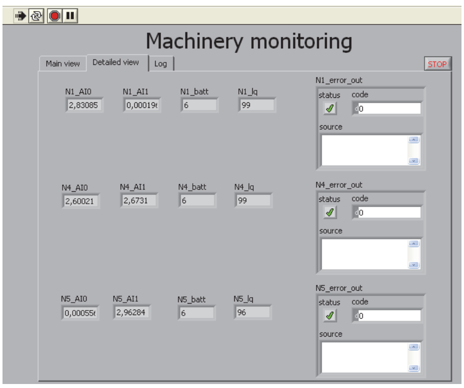

Fig. 9. UI, detailed view: battery energy and radio frequency quality information

Designed utilization monitoring model was presented to master students and a production company management.

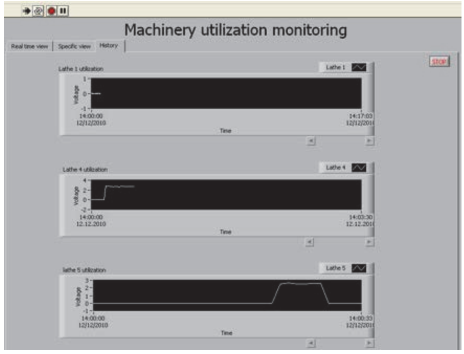

Fig. 10. UI, historical view: graphical presentation of workbenches utilization and pausing reason information

4. FEEDBACK AND DISCUSSION

Machinery utilization monitoring prototype was introduced to mechanical engineering master students, who were surprised that utilization monitoring is not widely used in manufacturing companies. It shows, that for master students, monitoring is one part of manufacturing and they are minded to use it in their further career.

Prototype was also introduced to a manufacturing company management. Compared with students, they were a little more discredited, but they decided to set up a prototype monitoring system to their shop floor cooperation with Tallinn University of Technology. It can be concluded that developed prototype model act as planned and it convinces company managers and students in its beneficial influence in real production. Furthermore, thanks for the model, monitoring system will be set up to the manufacturing company.

In sample model the state of the machine can be determined by measuring certain voltages. NI WSN node analogue voltage input channels were used for that purpose. In practical application it is unadvised to use shorter than 1 second sample times for NI WSN nodes, so AC signal measurement requires more complex measuring front-end schematics. There are industrially produced signal converters available and suitable for measuring currents and voltages in real production environment.

NI hardware and software are easier to use than typical WSN node (Berkeley node), as NI equipment is preinstalled and programming environment is graphical. Advantage in Berkeley nodes usage is lower price and wider opportunities in programming. For data collection and presentation, separate program must be used to achieve compact, well comparable and cognitive UI.

Next step in utilization monitoring is to set up monitoring system in shop floor and design advanced UI that can be used over the Internet.

5. ACKNOWLEDGEMENT

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

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PAPER IV

Aruväli, T.; Maass, W.; Otto T. (2014). Digital object memory based monitoring solutions in manufacturing processes. *Procedia Engineering*, 69, 449–458.

Available online at www.sciencedirect.com

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Procedia Engineering 69 (2014) 449 – 458

Procedia Engineering

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24th DAAAM International Symposium on Intelligent Manufacturing and Automation, 2013

Digital Object Memory Based Monitoring Solutions in Manufacturing Processes

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Abstract

Manufacturing processes monitoring is more than conventional machinery monitoring, it covers also a part quality monitoring and manual working processes monitoring. To explain it, a novel Digital Object Memory (DOMe) based model in automated surface roughness monitoring and data storage in turning is proposed. The model allows automated interaction between workpiece (WP) and machine tool using RFID based smart environment. As a result, WP on-board g-code for turning and machine tool based real time cutting signals are combined into algorithm to measure indirect surface roughness of WP. Moreover, surface roughness value for every cut can be stored on-board of WP to detect the WP history and quality all over the product life cycle. Also framework for DOMe based hand work station monitoring and assistance system is proposed. Smart environment creates compatibility between parts and products on working area to double check workers attentions and to give assistance to workers for avoiding mistakes.

Selection and peer-review under responsibility of DAAAM International Vienna

Keywords: Digital Object Memory; quality monitoring; human-machine interaction; Cyber Physical Production System

1. Introduction

Conventional machinery monitoring gives the utility only in narrow field in the whole manufacturing process. More advanced approach is needed to merge different processes and specific products dynamically with monitoring sensors and assisting environment to achieve maximum productivity all over the manufacturing process. Cyber Physical Production System (CPPS) concept [1,2] introduces the application of Digital Object Memory (DOMe)

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1877-7058 © 2014 The Authors. Published by Elsevier Ltd.
Selection and peer-review under responsibility of DAAAM International Vienna
doi:10.1016/j.proeng.2014.03.011

[3,4] that paves the way into augmented reality. Mechatronics and information technology have been the main drivers of monitoring development in manufacturing. Information technology new solutions together with more accurate sensors have given the option to collect data about processes, to follow state of processes over the Internet and to take fast real time decisions. Machining seems to be always close to production managers, wherever they are located.

Manual work can be improved using state of the art monitoring solutions. Machine tool monitoring concentrates mainly to the parts quality and machine tool components condition. Machining quality is influenced by several components (gears, bearings, cutting tool, machine tool rigidity, machining environment), but all in all cutting tool – workpiece (WP) contact point carries the most sensitive data [5] in part quality point of view, which can be monitored visually [6].

Machining quality is slowly changing compared to human action. Workers tend to make mistakes in monotonous work, but in changing working situation they need extra time for adaptation. The bigger is batch sizes, the more automated machining processes are required. But in last decade one-offs and small batches started to pave the way. It means a company can produce thousands of products, which are all different, but only slightly. It makes easier to change parts and to produce scrap. Moreover, manual work sections need monitoring as protective equipment usage reminder. It is easy to forget protective mask in gluing, protective glasses in laser working or ear protection in cutting. Nowadays, collecting of historical statistics is not the main idea of monitoring; instead, it is a tool for quality assurance. Its functions are rather to avoid reworking and wrong movements by giving real time feedback. Automatic assistance system with monitoring doubles the efficiency. Reminders and instructions, which are context sensitive, are the main force of increasing human work productivity and seamless work flow in shop floor.

In CPPS the physical work flow is combined with digital information flow that is both, machine and human readable. CPPS application, Digital Object Memory (DOMe) is the element that improves interoperability in shop floor environment. It is like a diary that in one hand conserves an object related historical and provenance information, but in other hand, it keeps collecting new information. Maximum effect rises, if a smart environment allows to communicate these objects to each other and to assist machines and humans to act in more efficient way. DOMe with supporting intelligent environment and sensors form an environment called augmented reality.

The aim of the paper is to introduce and discuss CPPS application DOMe based novel monitoring and assistance system solutions in machining output quality monitoring and in manual work section seamless workflow assurance and in human protection. The paper is organized as follows. Section 2 introduces the concept of CPPS and its application DOMe. Section 3 proposes a novel solution for DOMe based automated surface roughness monitoring and storage in turning. Fourth section describes DOMe based manual work station monitoring and assistance system.

2. Concept of DOMe in CPPS

2.1. CPPS

The idea of DOMe has grown up from German government national program Industry 4.0 [7,8]. The goal of the program is to pave the way for fourth manufacturing revolution. The first manufacturing revolution took place at the end of 18th century, when the steam and fluids found their way as energy carriers. The source of the second revolution was electricity as energy carrier and mass production as result. The third revolution took place in 1970-s, it was carried by developments in electronics and information technology that lead to manufacturing automation. Today, CPPS is on focus of this program as next revolutionary phenomena in production environment that helps to reduce the cost of production.

CPPS outlook is to integrate physical production system with cyber (digital) production system in the level, where distinguishing one or another is fuzzy. It means they are merged together as fully functioning flexible system. The production system develops towards concepts of Internet of Things (IoT) and All-IP. IoT main idea is that soon 90% of computers are embedded computers, also in production environment. They are integrated into products and parts that seem unnatural today. All-IP carries the same idea that everything around have IP address and Internet access capability. It goes beyond a manual human leveraged simple unilateral control, where information flow goes through human as center of everything. Conventionally, a human starts interaction, but according the idea, the things could communicate with each other to improve the result.

CPPS needs intelligent environment for communication. For instance, according to IoT a package of milk can communicate with transportation truck air conditioner to regulate the temperature, if needed [9]. Later, in store, a customer can get access to the milk temperature history and can evaluate, if he wants this milk or not. In the same way, also in production environment drives, components and parts can communicate with each other to plan production in optimal way, ensure the quality, reduce reworking and save production information for possible recalls.

CPPS can be naturally built on service oriented architectures [10]. It means, in shop floor planning, the focus is on services and hardware is secondary. Services library would work as app-s in smart phones. One of the main challenges utilizing above described environment is compatibility between different machine tool components, parts, tools and products. Potentiality lies on open standards and semantic information presentation. Semantic programming languages like Web Ontology Language or RDF [11] can be used, which bases to provenance of objects and object groups mutual relationships [9].

2.2. Concept of DOMe

Concept of DOMe was first mentioned by W. Wahlster in 2007 [12]. DOMe is the fruit of CPPS development. It supports the idea of communication between products, machine tools and humans. DOMe has a structured storage place for object related information that supports information usage over the object life time. DOM comprises hardware and software components, which together provide an open and universal platform for capturing and interacting with the digital information of connected objects - including storage, documentation and provision of information concerning actions an object is or might be involved in [13]. It is defined as follows: DOMe denotes of repository of digital data, which is linked with a physical artifact, and which is continuously enriched with data from entities that interact virtually of physically with the artifact [14].

DOMe is sometimes also called Digital product memory, but the expression Digital Object Memory is more correct if the memory is attached already in raw material or WP phase, when it cannot be called product yet. The main developer of DOMe has been J. Haupert [15] from German Research Center for Artificial Intelligence.

DOMe focuses to the product service oriented automation in manufacturing environment. Conventionally, a process have been the most important to optimize production. DOMe changes every product unique, every product from batch can be recognized personally. That is actually true, for instance cutting tools are in continuous wearing situation and every next part have probably lower surface roughness quality, until next cutting tool change. Also material heterogeneous structure, human interaction and storage conditions play an important role in part behavior and life time.

Semantic DOMe bases on Extensible Markup Language, which is both- human and machine readable language. Object Memory Model (OMM) defines DOMe structure and it is W3C open standard [16]. The fastest and the most convenient solution is to store a memory directly on object integrated device, usually on radio frequency identification (RFID) tag. As RFID tags memory is limited, therefore large data sets need to be saved outside of the object, to the back-end system, which can be accessed by link. Back-end system can be hold in Object Memory Server (OMS) [17]. OMS manages many different objects memories. For access to the server, URL address is used that starts with object ID and ends with specific memory name. Fast access information as working parameters are recommended to hold on object and monitoring larger data sets, which are not so critical, in back-end system [18]. Since, some input information (like g-code of the part) is confidential for a company; it can be encrypted for other users.

In projects carried on so far, mostly passive RFID tags are used as information storage place [19] but also more expensive WSN (wireless sensor network) based solution has been proposed [20]. WSN gives more options as attached sensors can measure the product related parameters and activate alarms or switch lights in certain conditions. Also some RFID tags are already equipped with sensors, but they also need extra energy source that changes them more expensive and massive.

A passive ultra high frequency RFID system consists of a transponder, also called a tag, and an interrogator, also called a reader. The reader provides power via RF energy, commands via protocol, and timing. The tag consists of an IC (integrated circuit) and an antenna. The tag communicates by modulating the IC impedance, which changes the scattering characteristics of the antenna, which can be detected by the reader. For an RFID tag to operate, the IC must receive sufficient power to run the circuitry and provide enough backscatter signal strength for the reader to detect the response. Regarding several systems it can be assumed that the system is limited in the forward channel (reader to tag), and if the tag responds, then the reader will detect the response. As is common with many antennas, the bandwidth of an RFID tag is typically limited by the impedance of the antenna. The reactive IC impedance can further aggravate this problem [21].

DOMe can be used over entire product life cycle; sample has been brought about pizza life cycle [22]. In manufacturing environment, DOMe equipped object is capable to order its own working according to previously saved specification, to collect monitoring information during its working about physical parameters, time and used machine tools and equipment. After production it can monitor its stock and transportation conditions. In store or in customer hands, it has ability to introduce its provenance and quality. Finally, it can be helpful if it is need to manage recalls or development of production process.

3. DOMe based surface roughness detection model in turning

According to the concept of DOMe, it should hold the information related with product processing and should collect information in time of processing. One of the first DOMe based prototype solution was presented in Hannover Messe Industrie 2010 fair by Stephan et al. [23]. It describes the processing of dietary supplements. In this prototype, a product is basically complemented from limited number of modules. WP owns on-product information about its modules by stored codes and after processing it is complemented with production time stamp. There is also mentioned that after milling, all relevant information regarding the successful processing is transferred to the on-product DOMe and available to the following manufacturing steps. But what information is needed and how to collect it, is not mentioned.

In CNC machining, feedback about correct geometry according tolerances is important. But also many of the physical characteristics (vibration, temperature, acoustics, current consumption) can be classified as useful quality descriptive monitoring information. One option is to compare for instance temperature in working zone and try to find irregularity. Since temperature is relatively slow changing characteristic, it cannot detect sudden impacts, but only the trend. On the contrary, vibration and acoustics are influenced immediately, if an impact appears. But usually temperature, vibration and acoustics threshold values are not specified and it is hard to define them during small batches. Much more informative is surface roughness value that is always comparable.

Surface roughness can be indirectly measured by evaluating in-process signal, cutting parameters, insert radius and machine tool stability coefficient [24]. According the concept, WP DOMe contains its working information. If the storage capacity is sufficient, instead of special codes for modular CNC machining, full machine readable code (G-code) can be stored in DOMe. G-code comprises the information about cutting parameters and treatable surfaces with their geometry. In-process signal can be measured by sensors, but placing sensors with energy consumption into every WP, is inconceivable. Cheaper solution is to merge sensors to CNC machine tool or cutting tool and change information between sensors, WP, machine tool and cutting tool. Read/write passive RFID tags or chips in above mentioned things and RFID transponder with antenna in near field create an intelligent environment for data transfer.

3.1. Sample case with model

As follows, sample DOMe based CNC turning case is described and analyzed. A WP needs to be cut according to the drawing (Fig. 1). Bold line presents the part; dash lines present the cuts and WP geometry change. Four cuts are needed to achieve the part with required surface roughness. Cuts no 1 and 2 are rough cuts and their surface roughness is not important. Cut 3 must give 10 point average surface roughness (Ra) at least 3.2 and cut 4 accordingly Ra 1.6.

WP has on-board DOMe that is structured to header, table of contents and blocks (Fig. 2). Header contains specific order related ID for every product. Table of contents makes the structure understandable for human and recognizable for objects. Blocks are divided to metadata and block payload data. According to OMM, metadata is ID, name, format, creator, contributor, title, description, type, subject and link. All the metadata blanks do not need to be filled. Every block payload contains information about specific processing operation. In this case, block 1 contains information about WP geometry, material and physical properties. Block 2 is divided into two parts. Part A contains instructions for processing (turning) and part B will be stored after the processing with monitoring information. Compared with open standard OMM, blocks are divided into two parts, to separate original DOMe data and collected information in the course of lifecycle. The rest of the structure remains the same.

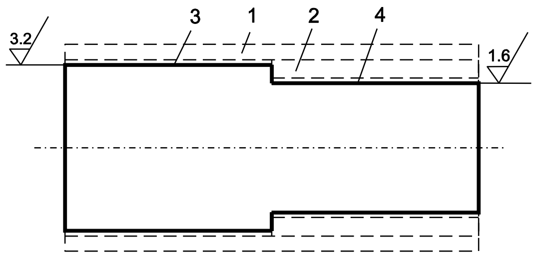

Fig. 1. Sample part cutting steps.

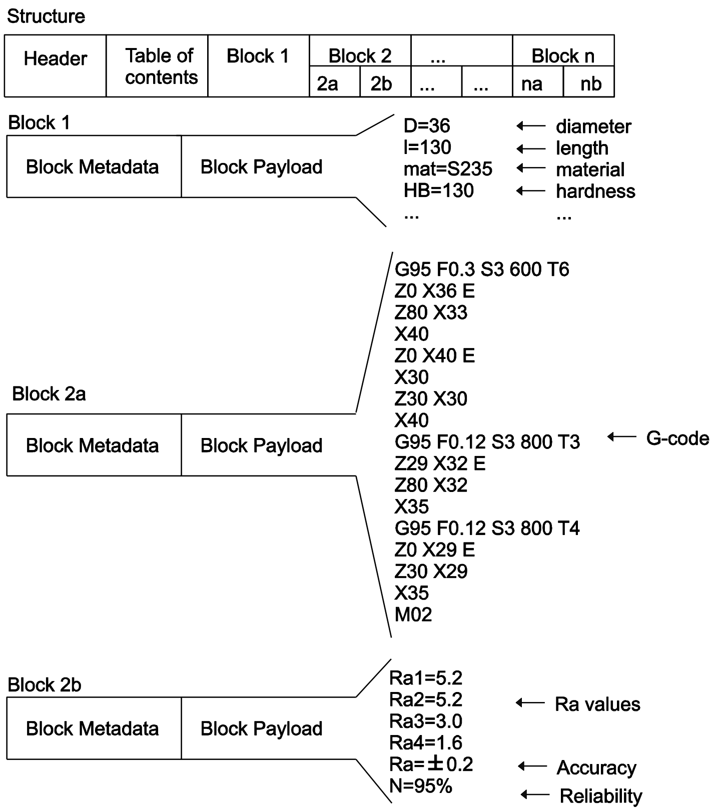

Fig. 2. WP DOMe structure.

In this case, block 2A contains g-code for the part turning. G-code shows that three different cutting tools are used to optimize tool inserts life time. First two cuts are rough cuts and their surface roughness result is not so important than removing enough material to be prepared for finishing cuts. For those cuts, fast and high productive tool is used. Subsequently, for cuts 3 and 4, two different finishing tools are used to achieve Ra 3.2 and Ra 1.6 accordingly.

If a cutting tool is placed to cutting position, intelligent environment activates a monitoring information transfer algorithm (Fig. 3). First, data is requested from WP and machine DOMe-s. According to received data, pattern is selected for surface roughness calculation. In the same time, in-process signal is sensed by sensors. If the signal is higher than specified silence level, it saves 0.25 sec signal for further analysis. Subsequently, analogue signal is converted to digital and Fast Fourier Transform is performed to make the analysis in frequency domain. Based on the signal and selected pattern, surface roughness is calculated continuously and saved to environment memory. Concurrently, calculated value is also displayed on screen to operator that has the biggest and fastest influence to the working process. If signal is measured as specified silence or lower, system asks if any surface roughness value has been already saved. If not, it means working is not started yet and loop is repeated. If yes, working is over, surface roughness values can be sent to WP DOMe into block 2B and loop can be stopped. To ensure the data flow, response from WP DOMe is asked about received data. Finally surface roughness values are deleted from environment memory. After turning operation, block 2B contains average Ra values for every cut, its calculation accuracy and reliability.

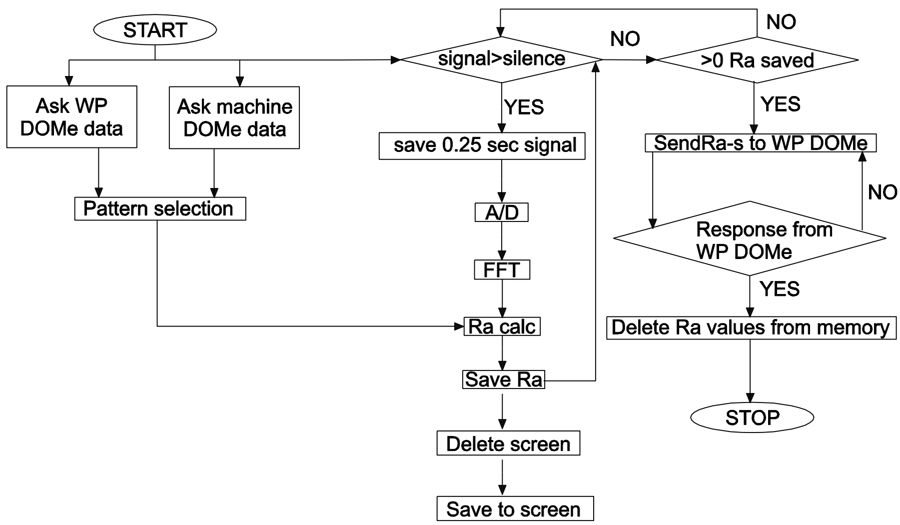

Fig. 3. Algorithm for interaction in surface roughness monitoring in turning.

3.2. Discussion

This solution helps to reduce the time of manual surface roughness measurement and save the quality values into the WP for the whole lifetime. It makes every part unique by its quality parameters. For instance in case of recalls, every part can be evaluated separately by customer according the manufacturer instructions and only potentially defective products are replaced, instead of full manufacturing set. Proposed model has potential in case of development of Flexible Manufacturing Systems, where introduction a new system to market still takes a time due to its complexity.

The solution was described theoretically, but implementation in shop floor needs further experimentation and deeper analyzes. For instance, G-code based solution is complicated to implement as it has more than 5000 different dialects. It means, basically every machine tool - CAM pair has different code. Hence, these codes do not differ completely. The most important, G and M code numbers still activate the same tasks, but one dialect adds row numbers, the other adds zero before one digit numbers etc. Important information as feed to estimate every cut time and theoretical surface roughness; rotation speed to choose the calculation pattern; and movement coordinates for cut counting and length are recognizable.

The other concern is suitable and reliable in-process signal feature extraction and analysis algorithm. Based on signal analysis, researchers have successfully worked out regression [25] and artificial neural network models (ANN) [26] to evaluate surface roughness, but their compatibility must be tested. Since regression and ANN models are based on large calculation sets, their eligibility for real time system must be tested.

4. DOMe based monitoring in manual work station

Machining operations have achieved a certain constant level in manufacturing and in last years it has not changed much. It is realized that everything cannot be fully automated and that humans still have an important role next to machine tools. Especially in changed manufacturing environment, with small batches and many one-offs. The smaller a batch, the more important is human presence. Humans are still more flexible than automated machine tools, but sometimes humans forget, mixe-up or misunderstand a task. For this reason, it is important to have an automated double check.

M. Schneider has described a case where a lady who needs to take medicals, gets a warning, if she wants to take pills with unsuitable drink [27]. This is DOMe use case in end user hands. Medicals and the drink both have a smart label with necessary information and dynamic environment with rules that allow context dependent assistance (ObjectRules) [28]. Also sample SemProM browser [29] has been built for this application. Similar context aware rule based assistance in manual work section would bring new certainty level in manufacturing. Innovative design methods are needed for building and evaluating such smart products [30].

4.1. Sample solution

This solution can be used in welding or gluing section. The principle is that every part, drawing, processing chemical/material and tool is equipped with DOMe that consist semantic information about its provenance and context based rules. Additionally, intelligent environment with access point needs to exist to provide energy and to provoke interaction between objects. Here, the meaning of provenance means an object material, ingredients and its physical and chemical properties. By knowing the materials, it can be checked if the parts can be welded or glued together. Additionally, welding electrode or glue suitability for these materials can be evaluated. To make this evaluation, context based rules are needed.

A context comprises three components: a user, objects and location. In shop floor, location defines the purpose, which processing will be used. According to knowledge about worker intensions, adequate rules can be used. Objects forward the facts about them shelves. Provenance information processing needs application knowledge to assist according to rules.

If worker enters to the environment, where protective equipment should be used, but worker does not do it, automatic assistance system gives an alarm. For instance, if on a gluing table is glue that contains toxic chemicals and protective mask cannot be found in environment, assistant gives a warning message.

All these rules can be either hard-coded or declaratively represented within knowledge representations. Knowledge representations are preferred if changes will occur on a regular basis [9]. For building repositories of knowledge representations, editors such as Protégé can be used. Protégé is an open-source platform that provides a suite of tools to construct domain models and knowledge-based applications with ontology´s. Protégé can be extended by way of a plug-in architecture and a Java-based Application Programming Interface for building knowledge-based tools and applications. Ontology describes the concepts and relationships that are important in a particular domain, providing a vocabulary for that domain as well as a computerized specification of the meaning of terms used in the vocabulary. Ontology´s range from taxonomies and classifications, database schemas, to fully axiomatic theories [31]. In

Protégé, Web Ontology Language (OWL) is used to describe classes, properties and their instances in semantic presentation (Fig. 4). In OWL, everything can be called Thing (materials, workers, properties). The glue contains certain chemicals. Sub class of Chemicals is ToxicChemicals that comprises list of toxic chemicals like dichloromethane. Thing ToxicMaterial is described as follows: ToxicMaterial is any Thing that has ingredient some ToxicChemicals. Having this semantic description in knowledge base, there is no need to describe fully every Thing, but just data about provenance (ingredients). If environment founds some material with chemical that is in list of ToxicChemicals, it searches protective mask DOMe from environment. If it is not presence, assistant gives a warning.

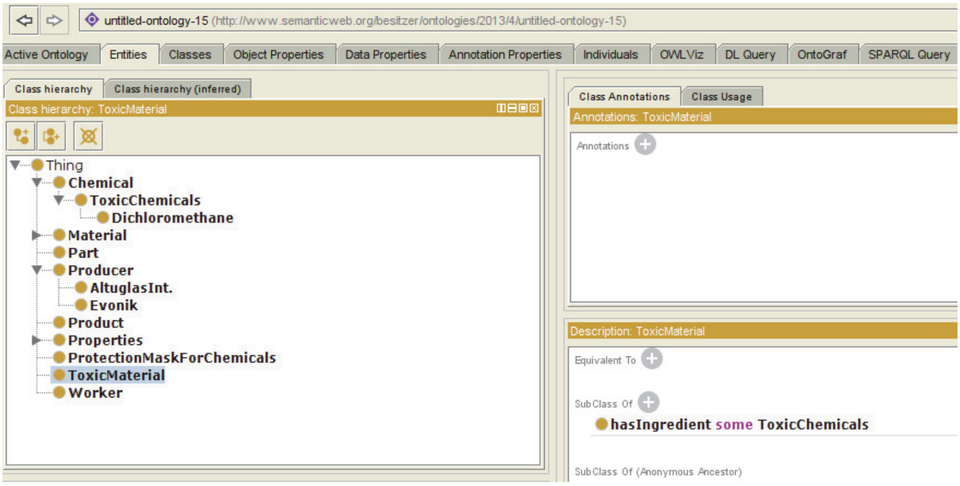

Fig. 4. OWL in Protégé platform.

In similar way, also processing suitability can be checked. If glue has knowledge about the materials that it is capable to glue and nearby parts material does not fit into the list, assistant gives a warning again to check the glue suitability.

Third hand work station possible application could be engineering drawing based. Engineering drawing memory in intelligent environment forwards the list of parts that are needed for a product. If some of the part in working environment is missing or some of them are unnecessary, automatic assistant system gives a notice. Last described application is crucial in production of one-offs, which have only slight modifications and for worker it is easy to change parts.

4.2 Discussion

This is theoretical solution, but it has great potential in CPPS. This solution facilitates production of small batches and helps to bring manual work back to developed countries. The aim is to achieve mass production like seamless work flow in small batches and one-offs.

Context, ontology and knowledge based monitoring with assisting real time feedback in manual work section provides information for fluent work flow. But implementation in shop floor needs preconditions. The broadcast area of intelligent environment is influenced by metals and it can cause noise. But this can be solved by using special Confidex Ironside™ tags that are not so sensitive with metals [21]. Implementing it in previously described way, needs uniform standard between different manufacturers and usage of DOMe on products. Also knowledge base enormous growth can damp down the idea by slowing down the interaction speed, which is essential to benefit the production. Above all, open standards are the bases for implementing such wide compatible system that across different production sectors and keeps the knowledge always up to date.

5. Conclusion

Automated communication and monitoring opportunities in shop floor are insufficient for seamless manufacturing of small batches and one-offs. Creating of RFID based intelligent environment spaces into shop floor, helps to bring the objects closer to each other by their interaction. One of the CPPS concepts, DOMe, is the tool for keeping all object related information in one compact and easy access storage place. As DOMe may also conserve the processing information, it can be used in quality monitoring in turning and for fault detection in hand work station. According to proposed model, surface roughness can be indirectly measured and stored in time of turning. In manual work station, workers mistakes can be cognitively pre detected and assistance provided to ensure seamless work flow. Proposed solutions help to save time of manual quality control and assure the process quality. So far, this is theoretical solution and experiments to support proposed models are next step of research. Proposed solutions have great potential, but there are also many obstacles that need to be solved to bring the implementation of the solution into reality.

Acknowledgements

This research was partly supported by Estonian Ministry of Education Research Project SF0140113Bs08, and European Social Fund's Doctoral Studies and Internationalization Programme DoRa, which is carried out by Foundation Archimedes.

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CURRICULUM VITAE

1 Personal data

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2 Education

Educational institution	Graduation year	Education (field of study/degree)
Tallinn University of Technology	2009	Product development and Production Engineering / Master of Science
Tallinn University of Technology	2005	Product development and Production Engineering / Bachelor of Science
Jüri Upper Secondary School	2001	Secondary education

3 Language competence/skills

Language	Level
Estonian	Fluent
English	Fluent
Russian	Average
Finnish	Basic
German	Basic

4 Special courses

Period	Educational or other organisation
2013	DAAAM International, 2nd DAAAM International doctoral school
2012	Doctoral School of Energy and Geotechnology II, Visual SLAM
2012	Doctoral School of Energy and Geotechnology II, Scientific trends in automation and manufacturing
2011	Doctoral School of Energy and Geotechnology II, Product development
2009	Doctoral School of Energy and Geotechnology II, Trends and sustainability of energy technology
2006	Syddansk Universitet, exchange semester

5 Professional employment

Period	Organisation	Position
2010–…	Nordic Plast OÜ	Project manager
2013	Universität des Saarlandes	Quest researcher
2007–2010	Laserstuudio OÜ	Project manager
2004–2006	Rinaldo Production OÜ	Press brake operator/ industrial engineer

6 Honours

Time	Issuer	Honour
2014	Estonian National Culture Foundation	BLRT fund stipend
2012	DAAAM International	Festo prize for young researchers and scientists
2010	DAAAM International	Festo prize for young researchers and scientists

7 Defended theses

Aruväli, T. (2009). Cable twister, master theses, supervisor Roosimölder, L.

Aruväli, T. (2005). Elevator ceiling and lightning development, bachelor theses, supervisor Roosimölder, L.

8 Scientific projects

Period	Topic	Project number
01.10.10–30.09.12	Research Based Competence Brokering (REBASING).	VERT498
01.06.10–31.05.13	Development of Innovative Business Models for Ensuring Competitiveness (INNOREG).	VIR478
2010–…	Energy efficient control of manufacturing modules (interdisciplinary project of Doctoral School of Energy and Geotechnology II)	DAR8130
01.01.09–31.12.12	E-manufacturing concept for SMEs	ETF7852

9 Publications

- Astapov, S.; Riid, A.; Preden, J.-P.; Aruväli, T. (2014). Industrial process monitoring by multi-channel acoustic signal analysis, *Proceedings of Doctoral Session of BEC 2014*, 209–212.

- Serg, R.; Aruväli, T.; Otto T. (2014). Power consumption based online condition monitoring in milling machine. *Online Proceedings of the 9th International DAAAM Baltic Conference "Industrial Engineering"*, [WWW] http://innomet.ttu.ee/daaam/proceedings/Production%20Engineering%20and%20Management/Serg.pdf (15.06.2014).
- Aruväli, T.; Maass, W.; Otto T. (2014). Digital object memory based monitoring solutions in manufacturing processes. *Procedia Engineering*, 69, 449–458.
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- Snatkin, A.; Karjust, K.; Majak, J.; Aruväli, T.; Eiskop, T. (2013). Real time production monitoring system in SME. *Estonian Journal of Engineering*, 19(1), 62–75.
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- Aruväli, T. (2012). Machinery real time monitoring application planning for workshop. *Proceedings: 11th International Symposium "Topical Problems in the Field of Electrical and Power Engineering",* 142–144.
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- Aruväli, T.; Serg, R.; Preden, J.; Otto, T. (2010). Smart dust applications in production environment. *Proceedings of the 7th International Conference of DAAAM Baltic "Industrial Engineering",* 572–577.

ELULOOKIRJELDUS

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2. Hariduskäik

Õppeasutus	Lõpetamise aeg	Haridus (eriala/kraad)
Tallinn Tehnikaülikool	2009	Tootearendus ja tootmistehnika/ tehnikateaduste magistri kraad
Tallinn Tehnikaülikool	2005	Tootearendus ja tootmistehnika/ tehnikateaduste bakalaureuse kraad
Jüri Gümnaasium	2001	Keskharidus

3. Keelteoskus (alg-, kesk- või kõrgtase)

Keel	Tase
Eesti keel	Kõrgtase
Inglise keel	Kõrgtase
Vene keel	Kesktase
Soome keel	Algtase
Saksa keel	Algtase

4. Täiendusõpe

Õppimise aeg	Täiendusõppe läbiviija nimetus
2013	University of Zadar, 2. DAAAM'i rahvusvaheline doktorikool
2012	Energia- ja geotehnika doktorikool II, Visual SLAM
2012	Energia- ja geotehnika doktorikool II, Teadusarengud masinaehituses ja tootmise automatiseerimises
2011	Energia- ja geotehnika doktorikool II, Tootearendus
2009	Energia- ja geotehnika doktorikool II, Visual SLAM, Energiatehnika arengusuunad ja jätkusuutlikkus
2006	Syddansk Universitet, välissemester

5. Teenistuskäik

Töötamise aeg	Tööandja nimetus	Ametikoht
2010–…	Nordic Plast OÜ	Projektijuht
2013	Universität des Saarlandes	Külalisteadur
2007–2010	Laserstuudio OÜ	Projektijuht
2004–2006	Rinaldo Production OÜ	Painutuspingi operaator/ tehnoloog

6. Tunnustused

Aeg	Väljaandja	Tunnustus
2014	Sihtasutus Eesti Rahvuskultuuri fond	BLRT fondi stipendium
2012	DAAAM International	Festo auhind noorteadlasele
2010	DAAAM International	Festo auhind noorteadlasele

7. Kaitstud lõputööd

Aruväli, T. (2009). Juhtmepööritaja, magistritöö, juhendaja Roosimölder, L.

Aruväli, T. (2005). Lifti toorlae ja valgusti arendus, bakalaureusetöö, juhendaja Roosimölder, L.

8. Teadusprojektid

Kestus	Teema	Projekti number
01.10.10–30.09.12	Teaduspõhise kompetentsi siire (REBASING).	VERT498
01.06.10–31.05.13	Innovatiivsete regiooniüleste konkurentsivõimet tagavate ärimudelite arendus (INNOREG).	VIR478
2010–…	Toote valmistusmoodulite energiatõhus juhtimine (Energia- ja geotehnika doktorikool II interdistsiplinaarne projekt)	DAR8130
01.01.09–31.12.12	E-tootmise kontseptsioon väike ja keskmise suurusega ettevõtetele	ETF7852

9. Publikatsioonid

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