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Development and Optimisation of Production Monitoring System

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Declaration:
I hereby 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 a doctoral or equivalent academic degree.

Aleksei Snatkin............................

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ALEKSEI SNATKIN

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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 the following [Paper I – Paper IV].

Paper I	Snatkin, A., Karjust, K., Eiskop, T. (2012). Real time production monitoring system in SME. In: *Proceedings of the 8th International Conference of DAAAM Baltic Industrial Engineering*, Tallinn, Estonia, 573-578.
Paper II	Snatkin, A., Karjust, K., Majak, J., Aruväli T., Eiskop, T. (2013). Real time production monitoring system in SME. In: *Estonian Journal of Engineering*, 19 (1), 62-75.
Paper III	Snatkin, A.; Eiskop, T., Kõrgesaar, K. (2014). Production monitoring system development. In: *Proceedings of the 9th International Conference of DAAAM Baltic Industrial Engineering*, Tallinn, Estonia, 198-203.
Paper IV	Snatkin, A., Eiskop, T., Karjust, K., Majak, J. (2015). Production monitoring system development and modification. In: *Proceedings of the Estonian Academy of Sciences*, 64 (1), 567-580.

The copies of the publications are included in the Appendices.

INTRODUCTION

Current trends in manufacturing engineering activities show the direction to stay competitive on the market and to deliver the maximum return on assets for production related companies. To achieve this, companies have to continuously search for innovative ways to improve their production processes, optimise current equipment and eliminate wastes of time and perform work in a faster and better way. Production processes should be effectively monitored and controlled to avoid malfunction and unplanned downtime. And reaction time to eliminate errors should be minimised.

With the growing complexity of production operations the scale and scope of the data to be monitored and controlled simultaneously increases. It requires the implementation of advanced automatic production monitoring systems.

Scarcity of resources and growing competition is a major challenge for the European manufacturing sector. To increase competiveness, manufacturing technologies should be continuously improved and updated. Production industry creates product related services such as maintenance, consulting, research, etc. Also, to not lose high value activities, new production processes and methods should be found. Many large enterprises have full time staff with expertise to manage specific applications, related to production monitoring, optimisation and data analysis. At the same time, small and medium sized enterprises (SME) that comprise a considerable part of most economies have to deal with the increasing number of data to be processed, but usually they cannot afford fully dedicated data experts and expensive information technology solutions, so it is very hard to track the important and process related information. In order to increase the competiveness of SMEs in the manufacturing industry, affordable solutions for process monitoring should be developed. To correct issues before they affect the production processes, there should be a move from a reactive to a predictive approach.

The reduction in hardware prices and extensive use of open-source software could increase the implementation of different production monitoring systems (PMS). From the other side decreasing the investment and implementation costs, will give a possibility for more companies to implement automatic machinery monitoring that provides an accurate overview of the shop floor activities, improving asset management, machinery utilisation and the stability of the production process.

Major challenges of such systems are to manage the substantial data volume that is generated, expensive industrial information technology (IT) infrastructure, lack of skilled employees and high implementation costs. An efficient PMS developed in this research should help to overcome the challenges described above.

As a few concepts consider predictive functionality, it was decided to apply predictive analysis based on the use of artificial neural networks (ANN). One of the ideas is to capture certain failure modes by tracking the changes in working regimes and comparing machine status.

The main objective of the research is to study and develop PMS with predictive functionality that operates in near real time, focusing on SMEs. To meet the objective such activities were performed: PMS concept development, system prototyping and mathematical predictive model development and optimisation. Novel solutions are presented in this research: as a concept of PMS with predictive functionality supported by the tool life prediction model.

Contribution of the thesis and dissemination

Continuous development of open-source production monitoring systems will open new potential for increasing productivity and the optimisation of production processes through the use of modern information and communication technologies (ICT).

This research can be especially recommended for production and maintenance managers, who are interested in implementing advanced monitoring and prediction systems.

The main results of the research have been published in peer-reviewed journal papers and presented in different conferences and seminars.

LIST OF ABBREVIATIONS

AJAX	Asynchronous JavaScript and XML
ANN	Artificial Neural Network
CNC	Computer Numerical Control
CPS	Cyber Physical System
DOMe	Digital Object Memory
ERP	Enterprise Resource Planning
GUI	Graphical User Interface
JSON	JavaScript Object Notation
ICT	Information and Communications Technology
IoT	Internet of Things
IP	Internet Protocol
IT	Information Technology
KPI	Key Performance Indicator
LLAP	Lightweight Local Automation Protocol
MES	Manufacturing Execution System
MSE	Mean Square Error
OEE	Overall Equipment Effectiveness
PMS	Production Monitoring System
PLC	Programmable Logic Controller
RMS	Root Mean Square
SCADA	Supervisory Control and Data Acquisition
SME	Small and Medium sized Enterprise
WSN	Wireless Sensor Network
XML	Extensible Markup Language

1 LITERATURE REVIEW

In recent years the production industry has continuously advanced through a growing degree of automation and integration of enterprise IT systems. Quick and reliable automatic data collection and analysis from the shop floor is one of the applications that has been in focus for many production companies and research institutions.

1.1 Background

Production monitoring is one of the Manufacturing Execution Systems (MES) functions. There are different definitions of an MES depending on the functionality of the systems existing on the market [Saenz de Ugarte *et al.*, 2009]. Together with the software companies, several major automation system providers offer their own MES solutions like Emerson, General Electric, Honeywell, Schneider Electric, Rockwell, ABB and Siemens. MES integrates separate data collection systems, links Enterprise Resource Planning (ERP) systems and integrates the control systems on the plant floor. The architecture of an MES is described in the standard of International Society of Automation ISA S 95. The different automation level hierarchy existing nowadays in the production industry is described in the figure below (Fig. 1.1).

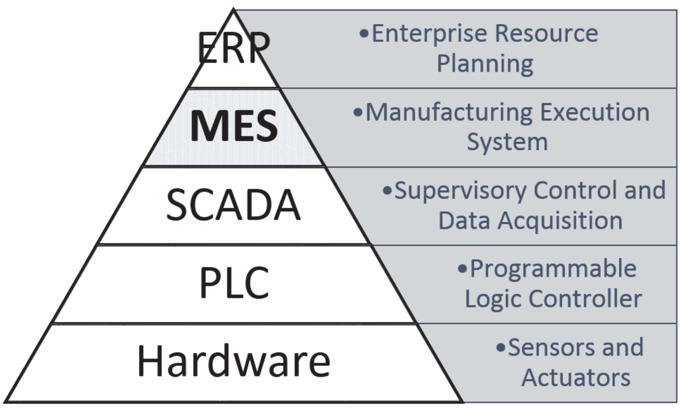

Figure 1.1 Automation Pyramid [Meyer et al., 2009].

There are a number of initiatives by large companies or governments existing in the manufacturing industry under different names like “Industrial Internet”, “Industry 4.0” particularly in Germany or even “Made in China 2025” proposed by the Chinese government. Together with different international projects like TAMS4CPS [TAMS4CPS, 2015]; CAPP-4-SMESs [CAPP-4-SMESs, 2012]; CyPhERS [CyPhERS, 2013], etc., and partnerships between the private and public sectors like ECSEL Joint Undertaking [ECSEL JU, 2014] they promote a deployment of Cyber-Physical Systems (CPS) [Lee, 2006; Lee *et al.*, 2015;

Monostori, 2014], where physical processes are monitored and controlled by the embedded computers with feedback loops. These smart systems will transform the production industry and create the future of automated manufacturing. The vision of CPS is going to blur the boundaries between different automation pyramid levels, which are described earlier. It should work not only for the new (state of the art) machinery, but also for the old ones, giving them more flexibility and productivity. Existing equipment with a long life span has to be updated to secure the required capabilities for the CPS.

The deployment of CPS requires the cross-linking of diverse databases, the availability of appropriate infrastructure and skilled employees. Significant changes have to be made on the shop floor, to achieve CPS-based production. Different existing technologies should be combined together and continuously updated. On the shop floor, production lines and machines should be interconnected with embedded sensors, advanced decision algorithms have to be applied, etc.

Industry 4.0 Global Expert Survey of 300 manufacturing leaders (from the US, Germany and Japan) that was carried out by McKinsey in 2015 [McKinsey, 2016] revealed that 76% of technology suppliers are prepared for Industry 4.0, but only 48% of manufacturers feel ready to apply it. According to the survey from the World Economic Forum 2015 report [World Economic Forum, 2015] the majority of the responders don't fully understand the effect of the industrial internet on their industries. This survey also describes major barriers to adopting the industrial internet (Fig. 1.2).

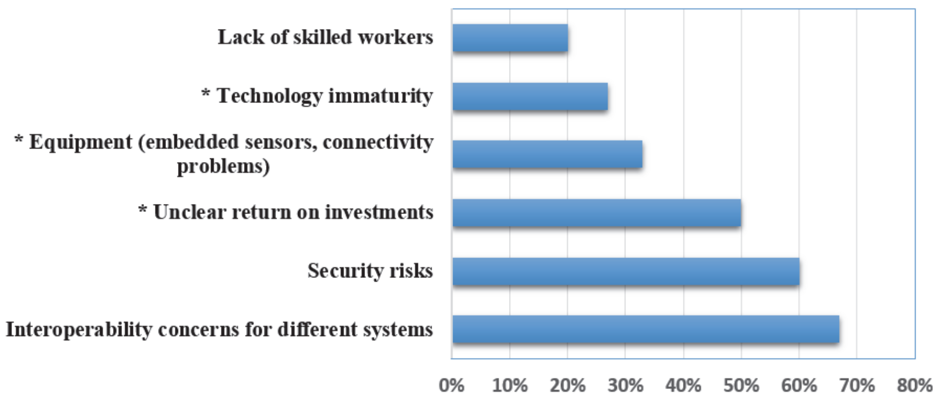

Figure 1.2 Key barriers to adopting the Industrial Internet, Europe [World Economic Forum, 2015].

These barriers should definitely be considered during the development of different platforms that will bring production closer to the idea of CPS. Specifically in this research, the focus is on lowering the investment costs to build a production monitoring system. One of the obstacles for many production companies has been to integrate such systems. That is why the proposed system is based on hardware (technology) available on the market. And monitoring equipment used is easy to embed to the machinery and production lines (e.g. wireless data transfer). All these will help to overcome barriers that are marked with an asterisk in Fig. 1.2.

Collaboration of different disciplines and applications should allow more flexibility in production. The ability to monitor machinery and production lines is key to opening the potential of digital technologies. The novelty behind it is the combination of different technologies available on the market, which were not widely used in the manufacturing industry and which can be implemented quickly with low cost.

To overcome the conservative culture of industrial companies in applying new technologies, low cost solutions should be developed showing the potential of existing ICT technologies. As an example, PMS should not be limited only by determination of the machinery status, but should be a more advanced system with predictive functionality, cloud technology, wireless connectivity etc.

Monitoring techniques have been widely researched over the years [Teti *et al.*, 2010]. Data can be collected directly from the machine controller or separate data acquisition system. Machine controllers mostly have a closed architecture system. And data collection through separate data acquisition systems often requires extensive expertise knowledge and high investment costs. The proposed system lowers these costs through the use of open source hardware/software and simple structure.

In order to form a unified picture, data from different sources may be combined and multi sensor data fusion applied [Khaleghi *et al.*, 2013].

In most cases collected data needs to be analysed to retrieve valuable information. A number of probability distributions have been proposed for modelling the tool life e.g. normal distribution, lognormal, inverse Gaussian, Bernstein, Gamma, exponential, Weibull [Vagnorius, 2010]. For tool estimation Taylor's equation is well known in more advanced extended models [Karandikar *et al.*, 2014]. The current approach described in this research also covers extreme exploitation conditions and is based on near real time data.

Web-based communication technologies and cloud-based services are used to enhance monitoring systems.

Due to the continued focus on production monitoring solutions from an academic and industrial perspective, similar concepts are recently presented by other authors [e.g. Tapoglou *et al.*, 2015; Mourtzis *et al.*, 2016]. In [Tapoglou *et al.*, 2015] the authors additionally concentrate on automatic cutting optimisation and G-code generation. In the current research such optimisation should be done by operators, however most of the monitoring data are collected automatically. In [Mourtzis *et al.*, 2016] the authors are highly focused on tool wear and maintenance, while the current research also includes a general production efficiency approach in addition to the tool life model.

1.2 Shop floor monitoring applications

Production monitoring information can be classified into two major groups: status of resources and status of jobs [Cowling *et al*., 2002] (Fig. 1.3). Status of jobs is related to processing time, production sequences etc. This overview of the production processes supports scheduling. Status of resources is related to the information concerning machinery, material and labour. Machinery is monitored to get the data about the tool wear and to provide the state of the tool or component and availability of machinery [Aruväli *et al*., 2012; Mehnen *et al*., 2014; Mourtzis *et al*., 2014]. Status of every machine or production line is supported by Key Performance Indicators (KPI) such as availability, performance, quality rate and Overall Equipment Effectiveness (OEE) [Singh *et al*., 2013; Lu *et al*., 2014]. There is also the standard ISO 22400:2014 that defines KPIs used in manufacturing operations management [ISO 22400 Standard, 2014].

Labour monitoring covers movement tracking and labour hours etc. Different indoor positioning systems are used to provide information about labour and the location of devices [Gu *et al*., 2009], human motion [Moeslund *et al*., 2006] and hand tracking [Yun *et al*., 2013] especially for manual assembly processes. Possible limitations and oppositions by labour unions and legislation related to labour monitoring is not discussed in this research.

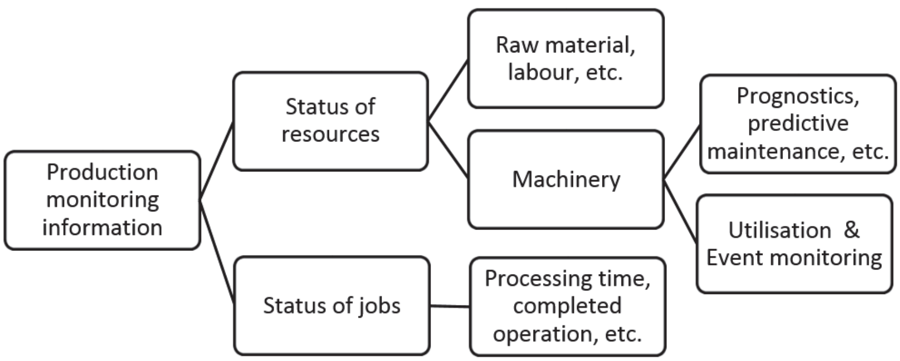

Figure 1.3 Example of production monitoring information components.

Working environment (noise, light intensity, vibration, magnetic field, ventilation, etc.) is related to the “status of resources” group, as it affects personnel comfort and safety. Automatisation and computerisation of manufacturing brought terms, visions and developments such as E-manufacturing [Koç *et al*., 2005; Lee, 2002], Smart Dust [Kahn *et al*., 1999], Digital Object Memory (DOMe) [Haupert, 2012; Aruväli *et al*., 2014], etc. All of these terms will determine how industrial production will be organised in the near future and what technologies will be used in the so-called “Smart Factory”. These benefits are based on the integration of the latest hardware and software developments, which are adapted to manufacturing industry requirements.

A wide range of machines may be used on the shop floor to perform different manufacturing processes: casting, moulding, machining, joining, painting, packaging etc. Rotating equipment used in machining processes has especially been researched in academia and the industry [Liang *et al.*, 2004] for many decades. A large number of sensor techniques has been investigated. The commonly used measures are: current, temperature, image, vibration, force, displacement etc. At the same time sensor fusion technologies may be used to combine more than one signal from several sources to form more reliable data [Lu *et al.*, 2014].

A variety of protocols are used to exchange the data between the equipment on the shop floor. This diversity complicates the connection of different systems. Different approaches exist to standardise it, as MTConnect [MTConnect, 2016] based on open XML, HTTP technologies. Machine tool builders like Mazak, DMG Mori Seiki and Okuma are already supporting the MTConnect standard. As a lot of machinery is not equipped with external communication capability, different remote machinery monitoring systems are developed [Deshpande *et al.*, 2011; Mori *et al.*, 2008; Shi *et al.*, 2006], which use different approaches (power signal analysis, etc.) to monitor equipment. The cost of integration of these solutions is directly related to the cost of additional software and hardware.

A lot of companies are providing different commercial production monitoring solutions with diverse functionality. As well as this many production companies are trying to implement their unique niche solutions. If more open-source designs are developed and shared, it will make these developments more accessible for SMEs and will help to implement more advanced systems with better calibration, statistic validation, etc.

1.3 Objectives of the research

Objective and activities:
The main objective of the research is to study and develop PMS with predictive functionality that operates in near real time, focusing on SMEs.
The main activities of the research are:

- Development of PMS concept;
- System prototyping;
- Predictive model development.

Scope and limitations of the research:
The design of the PMS system may be considered an introduction towards the integration of the new methodologies offered by cyber physical systems (CPS). System development requires interdisciplinary research: to incorporate data mining, software, hardware, user interfaces, ergonomics etc. As software architecture is not in the scope of this research paper, only basic software functions will be described. Developed production monitoring and a tool life prediction model were implemented and tested in the CNC 3-axis milling

machine and graphical user interface (GUI) for a production line and milling machine.

Main hypothesis of the research:

- Wireless production monitoring system can be built modularly and be easily expandable to collect and analyse production data;
- Discrete tool life analytical model for milling machine with support of artificial neural network model for determining dependence of the vibrations, temperature and current on process parameters (cutting speed, feed rate and cutting depth) can be developed;
- PMS can be built based on open-source hardware and software.

Structure:

The thesis is organised as follows: The present Chapter 1 outlines literature review and state of the art of shop floor monitoring activities. Chapter 2 gives a review of the basic design concept of the production monitoring system and prototyping. Chapter 3 provides data analysis and predictive modelling based on data collected by the designed production monitoring system. Chapter 4 summarises the research and points out further work.

2 DEVELOPMENT OF PRODUCTION MONITORING SYSTEM

There are many different types of production systems and processes in manufacturing companies. To increase shop floor transparency and productivity, the task is to integrate PMS into the production system. Different structures and methods are required to reach this goal. The chapter describes the basic design concept and prototype of the system.

2.1 General description of the production monitoring system

From the authors' point of view one of the main tasks of a PMS is to assist operators to respond timely to events that may affect the desired results [Paper I-II]. PMS is a tool that supports production operations by gathering vital data from the workshop, analysing and visualising it. This creates transparency of different processes and helps to determine the state of the operations and machinery, to avoid and recognise faults, to detect trends, etc. It is a valuable part of the production chain. Based on defined parameters and different rules (e.g. Western Electric rules [Western Electric, 1956], Nelson rules [Nelson, 1984]) the system monitors processes and informs operators [Paper IV].

Monitoring of different processes, creates a huge amount of various data and therefore there is a need to apply an intelligent system which supports data monitoring. The idea is not only to reduce the time to resolve problems, but also to eliminate problems through predictive functionality. It can eliminate unnecessary costs for premature maintenance. Continuous improvement of the operations and knowledge about the processes enhance production by reducing failures. Installation of the system should be carried out with minimal effort and cost. Cut down manual input should reduce administration. It can be viewed as a single solution to access different production equipment. Harmonisation of different IT systems already used on-site is a challenging goal. As PMS is used in an industrial environment, it should be robust and have acceptable accuracy.

Different researches that describe (near) real time shop floor monitoring approaches e.g. [Mourtzis *et al.*, 2016; Tapoglou et al., 2015] have similar concept structure and architecture as proposed system together with cloud infrastructure, web-based interface and open-source technologies.

In this research the framework is based on such steps as:

- Data acquisition and transfer,
- Analysis with predictive modelling,
- Visualisation,
- Data storage.

2.2 Basic design concepts

Production monitoring and prediction system should at least have data collection, analysis, visualisation and data storage modules as shown below (Fig. 2.1).

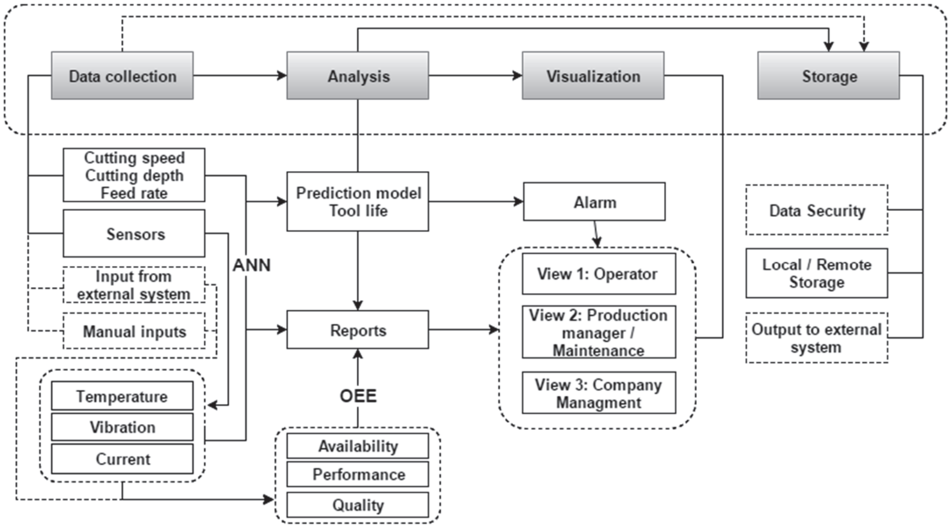

Figure 2.1 Proposed concept of a production monitoring system.

- *Data collection.* To detect different conditions data should be collected first. Different physical characteristics may be detected and measured by sensors. Wireless connectivity may support the connection of old, but usable equipment to the PMS [Aruväli *et al.*, 2011]. Low cost controllers such as Arduino give a possibility to develop a data collection module with small investments. There are even Arduino compatible PLCs offered on the market. At the same time it supports production companies to collect valuable information about machinery set up by operators and create knowledge repositories [Lemmik *et al.*, 2014b]. There should be transparency regarding what data are collected.
- *Data analysis.* Collected data may be analysed directly on the shop floor, or remotely through the use of cloud computing etc. There is a lack of smart analysis tools which could support the managing of big data in different manufacturing systems [Lee *et al.*, 2014]. Production machinery is adjusted according to the expert knowledge of operators even if it is not the optimal setting for the assigned task. The idea is to allow the production monitoring system to suggest the best settings based on the current or past conditions. The system should be self-learning. Different data analysis techniques are used to retrieve useful information

from the collected data [Paper IV]. Data should be filtered and turned into valuable information. Different open source libraries can be used.

- *Visualisation.* The main idea is to present complex data in a simple, logical and readable form. Data could be visualised on a stationary monitor or mobile device. Different level of GUIs should be presented e.g. Operator, Production Manager and CEO mode. The approach is to digitalise and visualise data in near real time. New forms of interaction between machinery and the operator such as augmented reality [Paelke, 2014] should be taken into consideration. Basic operation should be possible to do even if there is an interruption with the server connection (offline mode). And after synchronisation, the event (setting) should be delivered to the server. Visual awareness, user-friendly GUI as web or mobile apps, together with dynamic adapting of the representation method should be considered. Different images, graphs and charts should be used to manage reports and KPIs. In choosing visualisation equipment robustness must be considered in the industrial environment. Shneiderman's design principles [Schneiderman *et al.*, 2004] may be useful together with Hick's [Hick, 1952; Hyman, 1953] and Fitts' laws [Fitts, 1954; MacKenzie, 1992], when designing an interface [Paper IV].
- *Data storage.* Cloud Computing eliminates the need for high cost software and hardware installed on the premises for data storage and processing and simplifies future system expansion. Cloud computing can be divided into different services like: platform as a service, infrastructure as a service or software as a service [Yue, *et al.*, 2014]. A possible drawback is response time compared to local on-site server, as access is dependent on internet connection and security risks due to remote access. Local servers may be used as an option. If a huge amount of data is dynamically generated, it may be inefficient to transfer all the data directly to a cloud server as some of the data package may be lost due to network overload, etc. In this case pre-processing may be done on a local server. As an example Raspberry Pi (single board computer) receives data from the Arduino controller and logs it into the remote server with the possibility to save it on a local server which runs itself if connection is lost. After connection is restored the saved data is transferred to the remote cloud server. Additionally, the Arduino controller may have installed a memory card for logging as a fail-safe in the case of data connection failure between Arduino and Raspberry Pi.
- *Security.* With the growing digitalisation of data in manufacturing, online security is becoming a really important subject. Some manufacturing data collected on the shop floor can be of the same value as product design data which is normally protected as intellectual property. To prevent industrial espionage or even production sabotage, different security systems should be applied, such as encrypted wireless communication, backup, etc. Despite being related to Cloud Computing, security policies inside the company (e.g. system privileges/restrictions, event logs)

should exist to support data protection. And security systems should be developed from the very start of the design process [Wang *et al*., 2015]. Fault tolerances and reliability of the system should be analysed [Lemmik *et al*., 2014a]. Even though PMS does not apply new production settings directly, it still participates in decision making.

2.3 System prototyping

Wireless sensor network (WSN) was built based on the open source hardware platforms. The aim was to develop a low-cost and scalable platform. A single board computer Raspberry PI 2 (Model B) that is based on ARM Cortex-A7 CPU (900MHz quad-core) and 1GB RAM together with Arduino Leonardo microcontrollers based on ATmega32u4 (clock speed 16MHz) with 20 Digital I/O pins and 12 Analogue input channels were used. For wireless communication XRF radio modules were used, due to the simplicity of connection without end-user configuration or programming. This module operates at lower frequency (868 and 915 MHz) than widely used in the XBee modules (2.4 GHz). At the same time it has the same style pin layout as XBee. To connect the XRF module to Arduino and Raspberry PI 2 expansion boards were used.

Different sensors were connected to the Arduino controllers, like: waterproof temperature sensor DS18B20; adjustable infrared reflection sensor (3-80cm); current sensor SCT-013-100; humidity and temperature sensor DHT22 and 3-axis accelerometer (+-1.5/6g) MMA7361L. The hardware components used and the architecture of the system prototype are shown in Fig. 2.2 and 2.3, respectively.

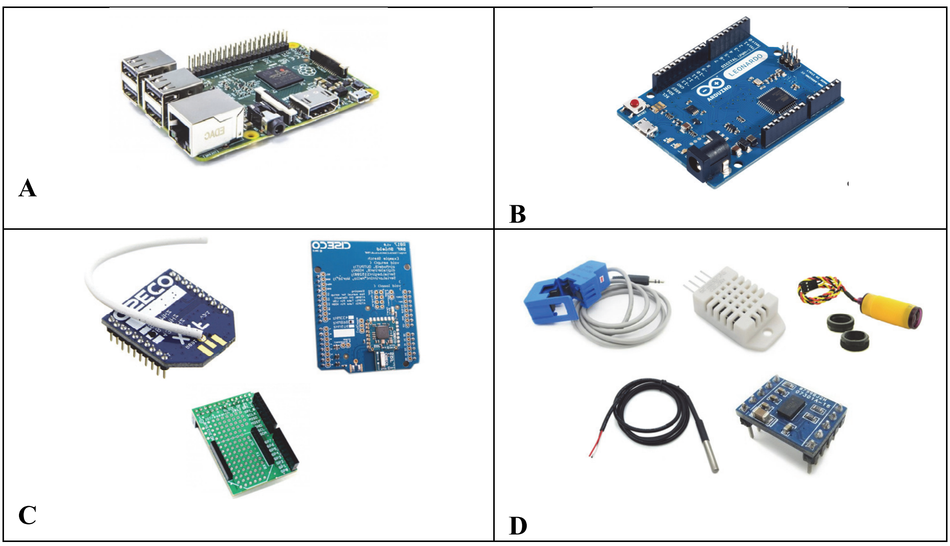

Figure 2.2 (A) Raspberry PI 2; (B) Arduino Leonardo; (C) XRF Radio module and Arduino/Raspberry extension Shields; (D) Current/Temperature/Infrared and Acceleration sensors.

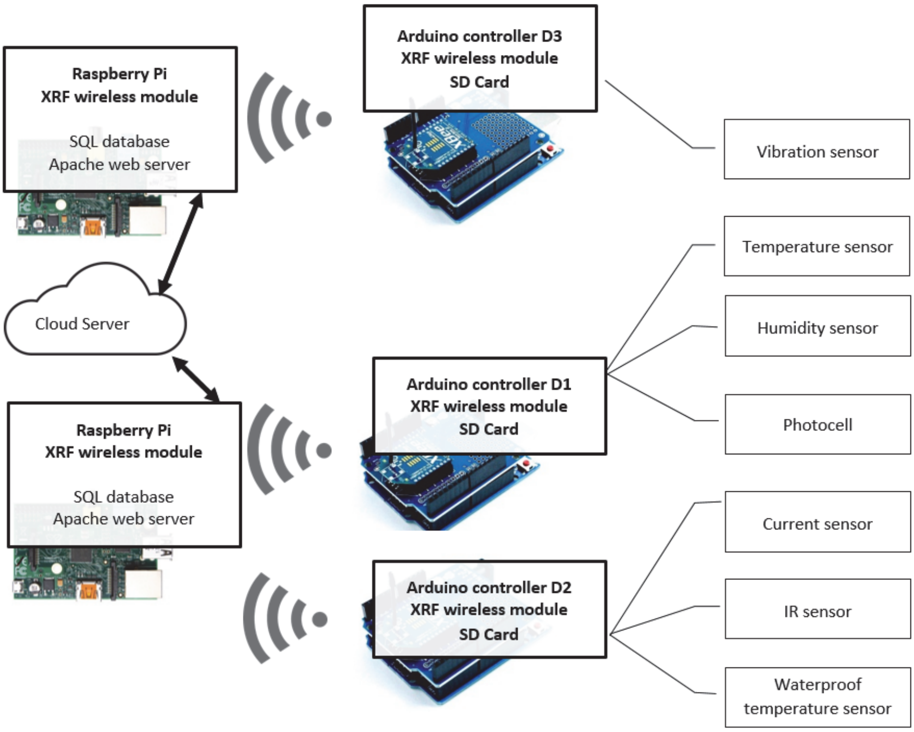

Figure 2.3 System prototype architecture.

The programming code was written in Arduino open source software and uploaded to the controller. Data were sent wirelessly through the XRF wireless module to Raspberry PI. LLAP (Lightweight Local Automation Protocol) was used. The Python programming language was utilised on a Raspberry PI to receive and save data to a local back up SQL database and also upload data to a remote server where calculations were handled. Each Arduino and Raspberry PI was equipped with memory cards for backup [Paper IV].

The web based GUI is under development with the support of JSON (JavaScript Object Notation) with AJAX (Asynchronous JavaScript and XML) technology to reduce the load on the server and the clients, as it allows specific objects to be updated in the GUI based on the specified interval and exchange data with a server asynchronously [Eiskop *et al.*, 2014]. Web-based approach allows the use of a wide range of devices with graphical interface support. Last development is based on an open-source Python Flask framework and AdminLTE template engine. A screen snapshot of the GUI for the milling machine that is under development is shown in Fig. 2.4. Availability calculation is based on current sensor measurements.

Proposed GUI may be presented as a three-level structure: View 1 - Operator mode; View 2 - Production manager mode; View 3 – Management mode. Operator mode shows workplace KPIs, produced items, quality inputs, system condition monitoring and machinery (or production line) utilisation. Production manager mode - combined department/workshop view, extended reports (performance comparison), reporting and statistics module, system administration. Management mode - production statistics, overall workshop performance, forecasts.

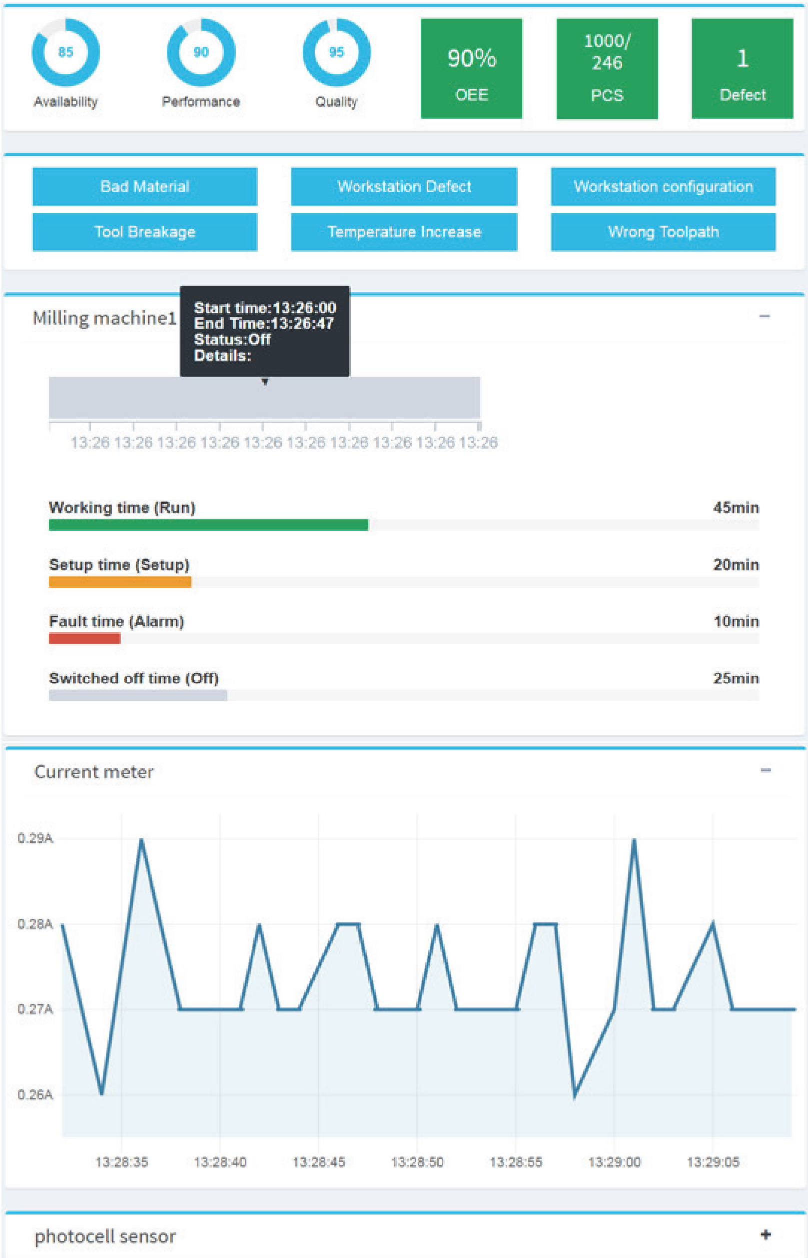

Figure 2.4 The web interface: View 1: Operator Mode.

Data presented to operators should be customised to be easy readable (e.g. qualitative measurements and KPIs), as it will be used in routine practice to get an indication of the job done and machine state. On the contrary, production managers should see more precise reports for groups of machines, the possibility to adjust limits and assign user rights, etc. Required KPIs and the calculation methods should be chosen together with the users. Most commonly KPIs are related to production output, quality, performance and availability. Additionally to availability (idleness; production; stoppage) the rate system must record the reasons for downtime. As an example, after each fault the operator selects the reason from the list, which may be updated by the production manager [Paper III-IV].

Administration tool phpMyAdmin was used to handle MySQL. Example of sensor values stored in the database are shown in Fig. 2.5 and 2.6.

Modify	sensor_id	sensor_id_name	sensor_name	sensor_model	chart_color	sensor_enabled
edit	1	D1S1	Photocell		E16F48	1
edit	2	D1S2	Potensiometer		6bcadb	0
edit	3	D1S3	Humidity	DHT22	7A95F1	1
edit	4	D1S4	Temperature	DHT22	279115	1
edit	5	D2S1	Temperature	DS18S20_Waterproof_OneWire	E148E1	1
edit	6	D2S2	Potensiometer			0
edit	7	D2S3	Current meter 100A	SCT013	e9977b	1
edit	8	SRV1CPU	Raspberry Pi CPU usage		000000	1
edit	9	D2S4	IR sensor		6f48e1	1
edit	10	D3S1	Accelerometer_X_axis	MMA7361		1
edit	11	D3S2	accelerometer_Y_axis	MMA7361		1
edit	12	D3S3	accelerometer_Z_axis	MMA7361		1

Figure 2.5 Example of sensors description in SQL database.

edit	id	sensors_sensor_id_name	reading	reading_time
edit	619230	D2S3	6.11	2015-01-06 12:29:30
edit	619246	D2S3	6.11	2015-01-06 12:29:32
edit	619266	D2S3	6.12	2015-01-06 12:29:33
edit	619282	D2S3	6.15	2015-01-06 12:29:34
edit	619298	D2S3	6.12	2015-01-06 12:29:36
edit	619318	D2S3	6.13	2015-01-06 12:29:37
edit	619334	D2S3	6.05	2015-01-06 12:29:38
edit	619352	D2S3	6.14	2015-01-06 12:29:39
edit	619372	D2S3	1.32	2015-01-06 12:29:41
edit	619388	D2S3	1.33	2015-01-06 12:29:42
edit	619426	D2S3	1.28	2015-01-06 12:29:45
edit	619442	D2S3	1.25	2015-01-06 12:29:46
edit	619495	D2S3	1.34	2015-01-06 12:29:50
edit	619527	D2S3	1.31	2015-01-06 12:29:52
edit	619547	D2S3	1.31	2015-01-06 12:29:54
edit	619563	D2S3	1.3	2015-01-06 12:29:55
edit	619583	D2S3	1.28	2015-01-06 12:29:56
edit	619603	D2S3	1.33	2015-01-06 12:29:57
edit	619619	D2S3	1.36	2015-01-06 12:29:59
edit	619639	D2S3	1.29	2015-01-06 12:30:00

Figure 2.6 Example of sensor readings in database.

Many sensors that are widely used with Arduino controllers already have sensor code libraries on different repositories like GitHub etc. So it saves a lot of time rather than writing the library from scratch.

In [Paper IV] development of GUI for production line for producing planed profiles in a wood-working company was additionally presented. The case study focused on creating a custom GUI for application in daily work to maximally eliminate paper reports. This development was later used as a basis for the milling machine GUI development. The idea was to present a shift overview with main indicators and stoppage reasons and time.

In the shift overview section, presented several key performance indicators that are the main measurements of the effective use of the planer line - meters produced during the shift and machine availability. Availability was calculated as the difference between the total shift time and the sum of stoppages. In connection with meters produced during the shift, an average production speed was presented.

Stoppage registration with time intervals and reasons was made by operators through data entry in the interface. Stoppages are displayed in chronological order and as a total summary overview.

The quality defects are registered by the quality inspector, who is inspecting each product that is produced. Raw material registration is done via a barcode scanner that reads the information from the pallet that is fed into the line.

Additionally it is possible to extract shift reports with all the registered data.

2.4 Conclusion of Chapter 2

PMS idea was described with basic functionality required [Paper I-IV]. As each production system has its own specifics with a huge variety of possible modifications, the system should be flexible for modifications. The trends are: web-based architecture, re-configurability, near real time performance, open-hardware and software, wireless connectivity, self-learning with predictive functionality, supported by cloud computing. Wireless PMS based on open source hardware and a software solution was developed and tested. Web based GUI was described. The tested system has a number of advantages, such as low-cost, scalable, compact and easy to maintain architecture.

3 PREDICTIVE MODEL DEVELOPMENT FOR TOOL LIFE

The current chapter is focused on one subtask of the product monitoring system: prediction of the tool/component life.

3.1 Short overview of tool life models

The manufacturing process can be improved by minimising the maintenance time of the machine tools or production line. Proper tool life modelling allows prediction of the need for maintenance, to avoid damage and breakdown of the tools/components.

First it is correct to note that the Taylor and Taylor extended models are still one of the most widely used models, despite extensive research in this area during the last decade [Li, 2012]. In [Suresh *et al*., 2014; Attanasio *et al*., 2013; Venkata Rao *et al*., 2014; Xu *et al*., 2011; D'Addona *et al*., 2016; Leone *et al*., 2011] the deterministic models are proposed for tool/component life modelling. The optimisation based lifespan model considering multiple cutting tools and strategies is presented in [Tapoglou *et al*., 2015]. In [Vagnorius, 2010] the detailed analysis of various lifespan models is performed and some shortcomings of the deterministic models are pointed out. In practice the process parameters fluctuate around setup values, the geometry and materials of the tools/components, also work-pieces, external conditions, etc. may vary. It should be mentioned that the lifespan of a tool/component lies in the range of a time interval rather than a fixed value. Thus, an alternate possibility is to employ stochastic life-span models [Li, 2012; Vagnorius, 2010; Li *et al*., 2013]. A number of probability distributions have been proposed for modelling the tool life like normal distribution, lognormal, inverse Gaussian, Bernstein, Gamma, exponential, Weibull, etc. However, some shortcomings can be observed [Vagnorius, 2010]:

- Application of normal distribution allows negative tool life to be obtained,
- Lognormal, also inverse Gaussian and Bernstein distributions yield unrealistic failure rate function increasing up to a certain time value and vanishing or decreasing to fixed value after this time value.

The Weibull distribution is found to be most suitable for modelling tool/component life in a number studies [Vagnorius, 2010], etc. By applying the two parameter Weibull distribution the reliability function of the tool/component can be written as

$$R(t) = e^{-(\lambda t)^{\alpha}} \tag{3.1}$$

In Eq. (3.1) α and λ stand for the shape and scale parameters of the tool/component. The effects of internal defects of the tool, external stresses, etc., are not included in Eq. (3.1).

Obviously, the probabilistic model Eq. (3.1) does not include directly processing parameters (cutting speed, feed rate, cutting depth, etc.) which may play a key role in tool/component wearing. Thus, in order to obtain a more adequate lifespan model the key parameters can be introduced in Eq. (3.1) through the shape and scale parameters α and λ, i.e.

$$\alpha = \alpha(S_{cs} f_{fr}, d_{cd}, ...), \ \lambda = \lambda(S_{cs} f_{fr}, d_{cd}, ...) . \tag{3.2}$$

In Eq. (3.2) S_{cs} f_{fr}, d_{cd} stand for the values of the cutting speed, feed rate and cutting depth, respectively. The functions in Eq. (3.2) can be approximated by linear or nonlinear regression, artificial neural networks, etc. However, the coefficients of the approximation model used should be determined from experiments. Note that since the function $R(t)$ represents reliability the value of the risk can be computed as $1 - R(t)$. The tool/component life T_R corresponding to fixed reliability value R_{fixed} can be expressed as:

$$T_R = \frac{1}{\lambda} \left(\ln \frac{1}{R_{fixed}} \right)^{\frac{1}{\alpha}} . \tag{3.3}$$

The tool life model proposed in the current study is based on a deterministic approach, but some uncertainty term is introduced. General description of the model is given in section 3.2 and a derivation in section 3.3.

3.2 The proposed approach for tool life prediction

The conceptual scheme describing an approach proposed for machine tool/component life prediction is shown in Fig. 3.1.

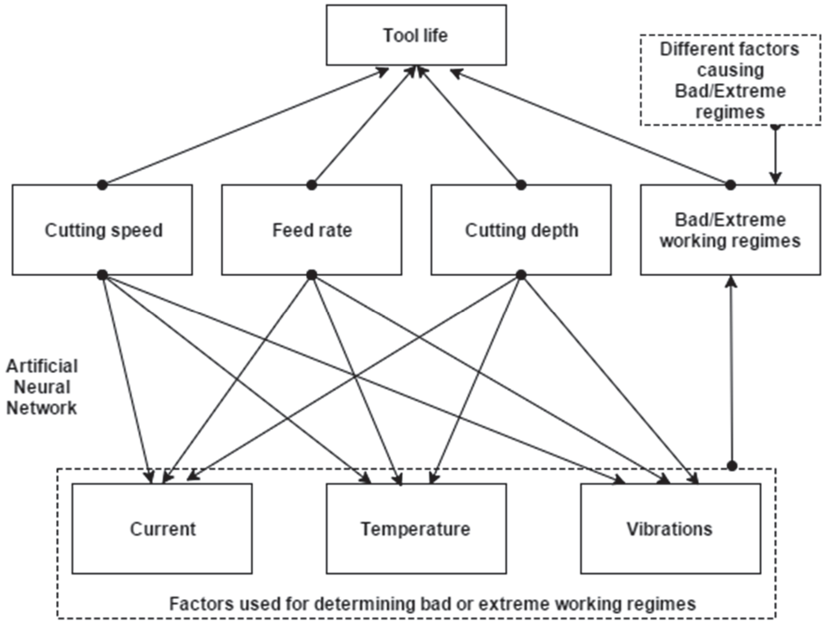

Figure 3.1 Scheme describing data analysis and modelling.

Different sensors were installed on the milling machine DYNA MECH EM-3116 to measure the temperature, current and vibration to be later used in predictive modelling. Current sensor was installed in the electrical cabinet of the machine on the main cable. Tool-work thermocouple was used in temperature measurements during metal cutting of St37-3 carbon steel. Entire tool was used as the one part of the thermocouple and the work piece as the other part. A vibration sensor was installed on the spindle housing.

It can be seen from Fig. 3.1 that according to proposed approach the tool life depends directly on processing parameters (cutting speed, feed rate and cutting depth) and indirectly (through working regimes) on vibrations, temperature and current, which in turn depend on processing parameters.

The predictive modelling performed herein consists of the following basic steps:

- development of analytical tool life prediction model covering the effect of the process parameters and working regimes,

– development of mathematical model for describing the dependence of the current, temperature and vibrations on processing parameters.

The illustrative diagram of the tool life prediction model derivation process is shown in Fig. 3.2.

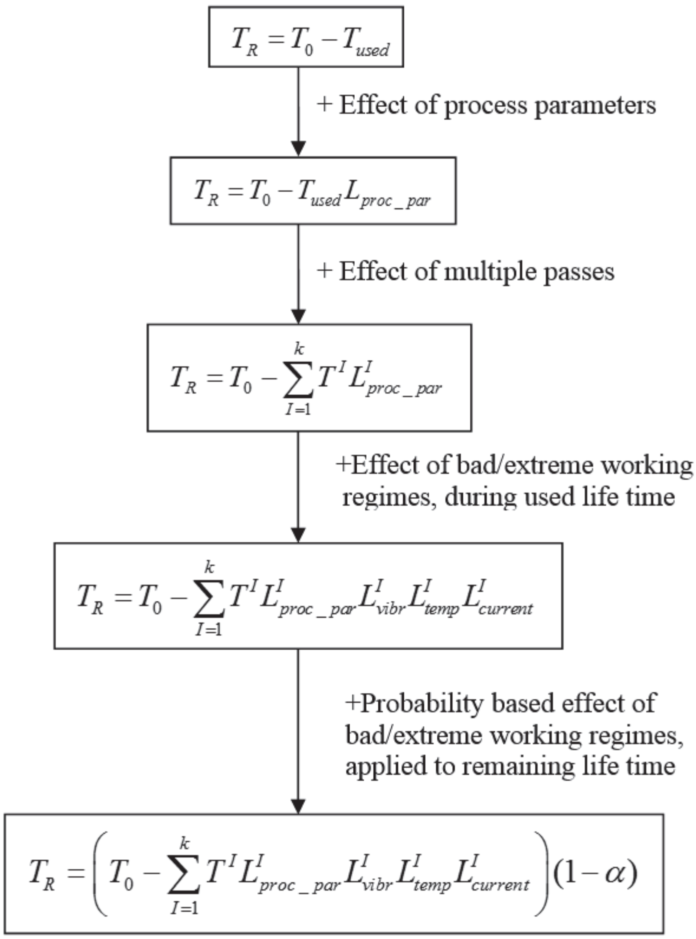

Figure 3.2 Tool life prediction model derivation process.

It can be seen from Fig. 3.2 that the derivation of the tool life prediction model is performed starting from simplest existing model and adding new features step by step. The detailed description of the tool life prediction model derivation process is given in section 3.3.

The conceptual scheme of the second basic task including data analysis and preparation is shown in Fig. 3.3.

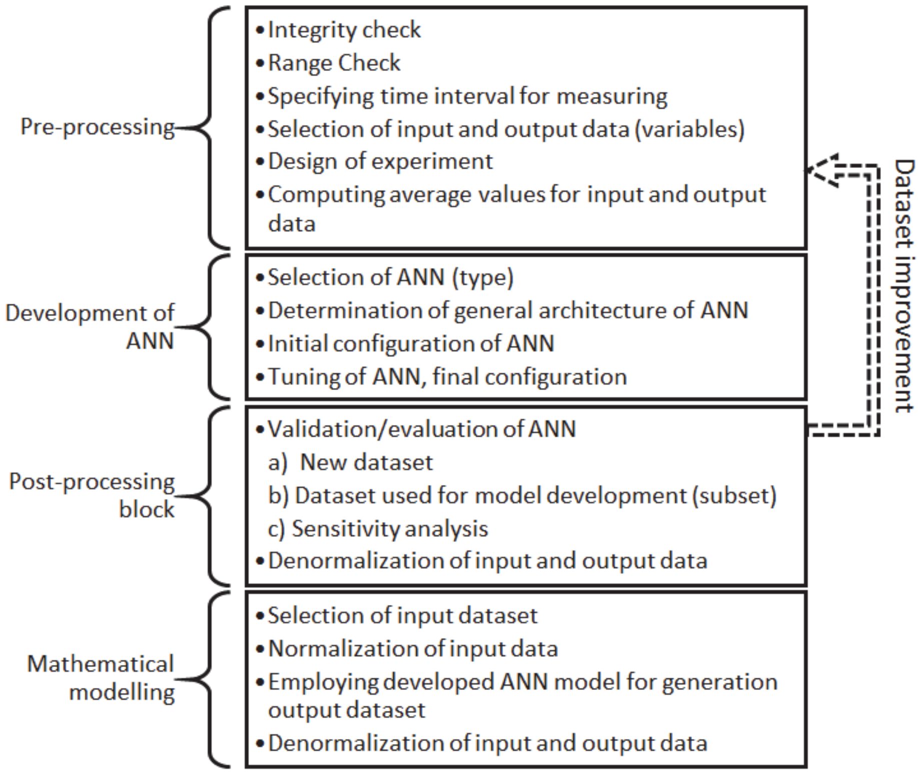

Figure 3.3 Development and exploitation of ANN model.

It can be seen from Fig. 3.3 that the selection of input and output data is not shown as the first step of pre-processing, since the collected dataset may include the model dataset as a subset. Thus, the data filtering is performed for all data collected, but certain characteristics are selected as variables of the mathematical model developed. The detailed description of the second subtask i.e. development and exploitation of the ANN based mathematical model is given in section 3.4.

3.3 Derivation of the tool life model

Let us start with the simplest relation for estimating tool life given as

$$T_R = T_0 - T_{used}, \tag{3.4}$$

where T_{used} is the time during which the tool is already used, T_0 and T_R stand for the initial and remaining life expectancy times of the, respectively. Obviously, the simple estimate Eq. (3.4) does not cover changing processing parameters, working conditions, etc. The robust estimate Eq. (3.4) can rather be employed in the case of fixed exploitation conditions where the process parameters (cutting speed, feed rate and cutting depth) are equal to reference values ($S^0_{cut\_speed}$, $f^0_{feed\_rate}$ and $d^0_{cut\_depth}$) determined experimentally or provided by the manufacturer

$$S_{cut\_speed} = S^0_{cut\_speed}\,,\; f_{feed\_rate} = f^0_{feed\_rate}\,,\; d_{cut\_depth} = d^0_{cut\_depth}\,, \qquad (3.5)$$

and the vibrations V, cutting temperature t, etc. parameters remain in a predefined range (i.e. the working regime is regular)

$$V \le V_0\,, \quad t \le t_0\,. \qquad (3.6)$$

Next, the tool life expectancy estimate Eq. (3.4) can be improved by introducing its dependence on processing parameters. Let start from the simplest case and consider first the effect of the cutting speed on tool life, only (one of the key factors influencing tool life). In the case of cutting speed value $S_{cut\_speed} > S^0_{cut\_speed}$ during used cutting time T_{used} the remaining tool life time T_R should be reduced, since the tool life is inversely proportional to cutting speed. Such behaviour of the tool life can be implemented by adding the coefficient to the subtractive term T_{used} in Eq. (3.4) as

$$T_R = T_0 - T_{used}\, L_{cut\_speed}\,. \qquad (3.7)$$

Obviously, $L_{cut\_speed} > 1$ if $S_{cut\_speed} > S^0_{cut\_speed}$ and $L_{cut\_speed} < 1$ if $S_{cut\_speed} < S^0_{cut\_speed}$. In the case of $S_{cut\_speed} = S^0_{cut\_speed}$ holds good $L_{cut\_speed} \equiv 1$.

The tool life coefficient L_{cut_speed} can be introduced as a ratio of the tool life functions corresponding to reference and actual cutting speeds as

$$L_{cut\_speed} = \frac{L_{cs}(S^0_{cut\_speed})}{L_{cs}(S^{actual}_{cut\_speed})}\,. \qquad (3.8)$$

In Eq. (3.8) the tool life function is given in general form $L_{cs} = L_{cs}(S_{cut\_speed})$ in order to cover various particular cases (linear, exponential, etc.). In the case Taylor lifespan model the function $L_{cs}(S_{cut\_speed})$ is given as

$$L_{cs}(S_{cut\_speed}) = \frac{C_1}{(S_{cut\_speed})^{1/n}}, \tag{3.9}$$

where C_1 and n stand for constants. Inserting Eq. (3.9) in Eq. (3.8) allows rewriting of the tool life coefficient L_{cut_speed} as

$$L_{cut\_speed} = \left(\frac{S^{actual}_{cut\_speed}}{S^{0}_{cut\_speed}} \right)^{1/n}. \tag{3.10}$$

For example in the case of $n = 1/3$ and $S^{actual}_{cut\_speed} = 2S^{0}_{cut\_speed}$ one obtains $L_{cut\_speed} = 8$ i.e. increasing the cutting speed twice will increase the used time of the tool or subtractive term eight times in Eq. (3.7) ($T_R = T_0 - 8T_{used}$).

The effect of feed rate and cutting depth on tool life can be introduced similarly to cutting speed by adding the corresponding tool life coefficients L_{feed_rate} and L_{cut_depth}, respectively. Thus, the Eq. (3.7) can be rewritten as

$$T_R = T_0 - T_{used}\, L_{cut\_speed}\, L_{feed\_rate}\, L_{cut\_depth}, \tag{3.11}$$

where the tool life coefficients L_{feed_rate} and L_{cut_depth} are assumed in general form as

$$L_{feed\_rate} = \frac{L_{fr}(f^{0}_{feed\_rate})}{L_{fr}(f^{actual}_{feed\_rate})},\ L_{cut\_depth} = \frac{L_{cd}(d^{0}_{cut\_depth})}{L_{cd}(d^{actual}_{cut\_depth})}. \tag{3.12}$$

The life modelling functions $L_{fr}(f_{feed\_rate})$ and $L_{cd}(d_{cut\_depth})$ in Eq. (3.12) are considered in general form in order to cover various particular relations (linear, exponential, etc.). It should be noted that the functions $L_{cs}(S_{cut\_speed})$, $L_{fr}(f_{feed\_rate})$ and $L_{cd}(d_{cut\_depth})$ depend on one parameter only and cannot cover well interactions between processing parameters. The shortcoming can be overcome by taking use the tool life coefficient L_{proc_par} and function $L_{pp}(S_{cut\_speed}, f_{feed\_rate}, d_{cut\_depth})$ depending on all processing parameters considered as

$$L_{proc\_par} = \frac{L_{pp}(S^{0}_{cut\_speed}, f^{0}_{feed\_rate}, d^{0}_{cut\_depth})}{L_{pp}(S^{actual}_{cut\_speed}, f^{actual}_{feed\_rate}, d^{actual}_{cut\_depth})}. \quad (3.13)$$

Obviously, the condition Eq. (3.13) covers directly the Taylor extended tool life model if the function L_{pp} is selected as

$$L_{pp} = L_{Taylor} = \frac{C}{(S_{cut\_speed})^{1/n}(f_{feed\_rate})^{q}(d_{cutting\_depth})^{r}}, \quad (3.14)$$

where L_{Taylor} is an expected life time of the tool, C , n, q and r stand for constants. The tool life functions L_{fr} and L_{cd} introduced in Eq. (3.12) can be defined similarly to L_{cs} given by Eq. (3.9), but in latter case there is needed additional constraint on constants to match the Taylor extended model uniquely.

In general the function $L_{pp} = L_{pp}(S_{cut\_speed}, f_{feed\_rate}, D_{cut\_depth})$ can be modelled by applying nonlinear regression, ANN, etc. similarly as done for tool wear in [Suresh *et al.*, 2014, Attanasio *et al.*, 2013]. Thus, exchanging the product of tool life coefficients $L_{cut\_speed}, L_{feed\_rate}, L_{cut\_depth}$ with one multi-parameter coefficient L_{proc_par}, defined by Eq. (3.13), will make the tool life model Eq. (3.11) more flexible.

$$T_R = T_0 - T_{used} L_{proc\_par}, \quad (3.15)$$

In order to cover multiple passes of the tool the Eq. (3.15) can be completed as [Snatkin *et al.,* 2013, Tapoglou *et al.*, 2015;]

$$T_R = T_0 - \sum_{I=1}^{k} T^I L^I_{proc\_par}. \quad (3.16)$$

In Eq. (3.16) T^I is the length of the *I*-th time interval during which the tool is used and k is equal to total number of time intervals used ($\sum_{I=1}^{k} T^I = T_{used}$).

Next, it is assumed in the current paper that the life of the tool is affected by bad/extreme working regimes. These regimes are detected by un-normal high values of the vibrations, temperature and current. Thus, the effect of bad/extreme working regimes is introduced in the tool life model Eq. (3.15) through coefficients L^I_{vibr}, L^I_{temp} and $L^I_{current}$ as

$$T_R = T_0 - \sum_{I=1}^{k} T^I L^I_{proc\_par} L^I_{vibr} L^I_{temp} L^I_{current} . \tag{3.17}$$

The coefficients L^I_{vibr}, L^I_{temp} and $L^I_{current}$ are defined as

$$L^I_{vibr} = \frac{V^I}{V_0^{discrete}}, L^I_{temp} = \frac{t^I}{t_0^{discrete}}, L^I_{current} = \frac{C^I}{C_0^{discrete}} . \tag{3.18}$$

In Eq. (3.18) V^I, t^I, C^I stand for the actual values of the vibrations, temperature and current in the time interval *I* and $V_0^{discrete}, t_0^{discrete}$, $C_0^{discrete}$ for predefined discrete values of the same variables corresponding to normal/reference working regime. The working regimes are determined based on measured values of the vibration, temperature and current (monitoring is performed by use of equipment described in Chapter 2). The discrete values for the vibration, temperature and current implementing the working regimes are introduced as

$$V^I = \begin{cases} V_0^{discrete} & if \quad V_{avg} \le V_0 \\ V_1^{discrete} & if \quad V_{avg} \in \left(V_0; V_1\right] \\ \ldots & \ldots \quad \ldots \\ V_M^{discrete} & if \quad V_{avg} \in \left(V_{M-1}; V_M\right] \end{cases}, \tag{3.19}$$

$$t^I = \begin{cases} t_0^{discrete} & if \quad t_{avg} \le t_0 \\ t_1^{discrete} & if \quad t_{avg} \in \left(t_0; t_1\right] \\ \ldots & \ldots \quad \ldots \\ t_M^{discrete} & if \quad t_{avg} \in \left(t_{M-1}; t_M\right] \end{cases}, \tag{3.20}$$

$$C^I = \begin{cases} 0 & if \quad C_{avg} \le C_{busywork} \\ C_0^{discrete} & if \quad C_{avg} \in \left(C_{busywork}; C_0\right] \\ \ldots & \ldots \quad \ldots \\ C_M^{discrete} & if \quad C_{avg} \in \left(C_{M-1} C_M\right] \end{cases}. \tag{3.21}$$

In Eq. (3.19)-(3.21) the index ‘discrete’ refers to predefined discrete value of the variable for particular interval (regime) and the index ‘avg’ to the average value. The regime with low vibration value not exceeding V_0 is considered as reference regime, where vibration does not cause extra wear of the tool/component. The vibrations corresponding to the following regimes with increasing indexes $i=1,...M$ have increasing impact on tool/component wear. The reasons of the occurrence of bad/extreme working regimes may be different, but most commonly related to failures of the machine components (ball-bearing, etc.), also some external factors. The regimes for temperature and current are introduced similarly (reference regime with $t \le t_0$, etc). The decision for determining the regimes are made on base of the average values of the process parameters. The value of the vibration is characterized by module.

In the following the behaviour of the discrete variables L_{vibr}^I is discussed in details. First, if the average value of the vibrations belongs to the interval $\left[0;V_0\right]$, then it follows from Eq. (3.18) and Eq. (3.19) that the value of the coefficient $L_{vibr}^I \equiv 1$. Due to increasing values of the V_i ($i=1,...M$), the corresponding values of the coefficient L_{vibr}^I are increasing (Eq. (3.18), Eq. (3.19)) and thus satisfy the condition $L_{vibr}^I > 1$. In practice it means occurrence of higher vibration levels (regimes) and higher tool wearing rates.

The effect of the second and third discrete factors is described in similar manner. It just has been assumed that in the case of $C_{avg} \le C_{busywork}$ the tool works on busywork regime without wearing, thus $C^I = 0$ and $L_{current}^I = 0$ (see Eq. (3.21), (3.18)).

Finally, tool life model Eq. (3.17) has been completed by introducing the stochastic term α representing the additional wearing caused by bad/extreme working regimes occurring during the remaining life expectancy time of the tool as

$$T_R = \left(T_0 - \sum_{I=1}^{k} T^I L_{proc\_par}^I L_{vibr}^I L_{temp}^I L_{current}^I \right)(1-\alpha), \tag{3.22}$$

where

$$\alpha = \sum_{k=1}^{M} \left[P(V_{k-1} < V_{avg}^I \le V_k) V_{k\_0} + P(t_{k-1} < t_{avg}^I \le t_k) t_{k\_0} + P(C_{k-1} < C_{avg}^I \le C_k) C_{k\_0} \right], \tag{3.23}$$

$$V_{k\_0} = \frac{V_k^{discrete} - V_0^{discrete}}{V_0^{discrete}},\ t_{k\_0} = \frac{t_k^{discrete} - t_0^{discrete}}{t_0^{discrete}}, C_{k\_0} = \frac{C_k^{discrete} - C_0^{discrete}}{C_0^{discrete}}. \tag{3.24}$$

In Eq. (3.24) the probability of the realization of vibration regime *k* is denoted by $P(V_{k-1} < V_{avg}^I \le V_k)$ and can be computed as ratio of the summarized time when the vibration regime *k* occurred and total time. The probability of the realization of the temperature and current regimes *k* can be computed similarly. Also, in the case when several bad/extreme regimes occur simultaneously (vibrations, temperature, current) here is considered effect of regime with highest coefficient (L^I_{vibr}, L^I_{temp} or $L^I_{current}$), only in order to avoid overestimating effect. Such an approach explains why relation Eq. (3.23) does not include probabilities of multiple simultaneous bad/extreme regimes.

It should be noted, that in the case of normal working regime and values of processing parameters equal to reference values given by Eq. (3.5) during whole processing time the proposed discrete tool life forecast model (3.22) reduces to the widely used simplest tool wearing model (3.4).

Such an approach is introduced due to the fact that in a real manufacturing process the values of the vibrations, current and temperature are varying in certain range (class, domain).

Development of the prediction tools performed can be considered as preliminary work for further optimization of the tool maintenance time, etc. Due to the presence of discrete valued parameters the traditional gradient based optimization algorithms are not applicable for minimization of the maintenance time of the tool. However, the hybrid genetic algorithm based global optimization techniques, developed by workgroup for wide class of engineering problems [Herranen *et al.*, 2011; Majak *et al.*, 2010a; Kers *et al.*, 2010; Majak *et al.* 2010b; Lellep *et al.*, 2000], can be adopted for particular problem considered.

3.4 Mathematical model for vibration, temperature and current

Let us proceed from the conceptual scheme shown in section 3.2 (Fig. 3.3). The following input and output data are considered:

- input data,
    - revolutions per minute (rpm),
    - cutting depth,
    - feed rate,
- output data,
    - the temperature,
    - current,
    - vibrations in x, y, z directions.

The data measured during real time monitoring process have been validated in regard to consistency and range. The missing and inaccurate values that are presented in data due to packet loss (wireless data transmission) and node failures (like temperature and current values out of defined range) were deleted. Despite real time monitoring capabilities the time intervals between data measurement and storage are introduced in order to keep the capacity of the dataset in reasonable limits.

According to Fig. 3.3, next the design of experiments (DOE) has been performed. Different DOE methodologies are available like full factorial design, central composite design, Taguchi design, etc. Full factorial design was chosen due to the relatively small number of levels for design variables used. Full factorial design provides high accuracy but may become infeasible (expensive) if there is a large number of factors. Real time data collection of production process gives thousands of results for each point of selected dataset. That is why the average values of the filtered data have been computed and used in further modelling. Thousands of repetitive experimental data points are covered by the dataset with a capacity of 48. The levels used for input data are depicted in Table 3.1. The full factorial design of experiment has been applied using three levels for spindle speed and four levels for cutting depth and feed rate. In Table 3.2 the average values of the vibrations, cutting temperature and current are shown. Here the value of cutting speed is fixed and the values of the cutting depth and feed rate are varied.

Table 3.1 The design variables and levels used.

Rotational speed (min^{-1})	**Cutting depth (mm)**	**Feed rate (mm/min)**
300	0.5	50
400	1.0	80
500	1.5	120
	2.0	150

Table 3.2 Sample dataset of averaged values.

Rotational speed (min^{-1})	**Cutting depth (mm)**	**Feed rate (mm/min)**	**Vibration 1g ($9.8m*s^{-2}$) = 100**	**Temperature (ºC)**	**Current (A)**
300	0.5	50	95.38983	142	6.21779
300	0.5	80	95.60138	150	6.24152
300	0.5	120	95.88618	159	6.24371
300	0.5	150	95.83397	165	6.24230
300	1	50	95.77639	160	6.26798
300	1	80	95.85723	164	6.26352
300	1	120	95.82442	168	6.40059
300	1	150	95.97473	179	6.41408
300	1.5	50	95.85072	180	6.37793
300	1.5	80	95.61432	180	6.48832
300	1.5	120	95.63406	181	6.69513

300	1.5	150	95.44471	182	6.68246
300	2	50	94.15741	182	6.53259
300	2	80	95.35855	183	6.77634
300	2	120	95.32091	188	6.95217
300	2	150	95.32969	197	6.99643

The data preparation module has been completed by normalisation of the input and output data using the following Eq. (3.25) and Eq. (3.26):

$$X_{i,N} = \frac{x_i - x_{i,\min}}{x_{i,\max} - x_{i,\min}}, \tag{3.25}$$

$$F_{i,N}(\bar{x}) = \frac{f_i(\bar{x}) - f_{i,min}(\bar{x})}{f_{i,max}(\bar{x}) - f_{i,min}(\bar{x})}, \tag{3.26}$$

where x_i and f_i stand for input and output variables, respectively and $\bar{x}$ is a vector of input variables. The normalised input and output variables are introduced as $X_{i,N}$ and $F_{i,N}(\bar{x})$. The values of normalised input data $X_{i,N}$ remains in the range of [0,1], but the value of the normalised output data may slightly exceed the limits of the range [0,1], since the maximum and minimum values of the output data are as rule an estimate for upper/lower bound rather than exact values of upper/lower bounds.

Different mathematical models can be found in literature for response modelling: linear / nonlinear regression, Gaussian process regression, artificial neural networks, etc. In the current study the back-propagation ANN is utilised for modelling the relations between input and output data. It has been shown in [Attanasio *et al.,* 2013] that in the case of similar problems (tool wear models) ANN results outperform those obtained by use of nonlinear regression. However no general rules for the best architecture of the ANN, can be found in the literature. The accuracy and robustness of the model are used as criteria for determining the suitability of the used ANN. Different approaches exist for determining the architecture of the network for the approximation of different functions [Gnana Sheela *et al*., 2013]. It has been proven that an ANN with a single hidden layer can approximate any continuous function accurately on a compact set and an ANN with two hidden layers can approximate any function to arbitrary accuracy [Heicht-Nielsen, 1989]. In the current study the following formulas are considered to involve the capacity of the training data [Gnana Sheela *et al*., 2013]:

$$N_h = \left(N_{in} + \sqrt{N_{tr}}\right)/L, \tag{3.27}$$

$$N_h = C(N_{tr}/(N_{in} log(N_{tr}))^{1/2}, \quad (3.28)$$

where L and N_{tr} stand for the number of hidden layers and the capacity of the training data, respectively. The number of neurons in hidden and input layers are denoted by N_h and N_{in}, respectively. The starting point is determined by the Eq. (3.27), next the number of hidden layers is increased up to the upper bound set by the right hand side of Eq. (3.28). The network design is finalised if increasing the number of neurons does not improve the accuracy of the results. Two transfer functions are validated (the hyperbolic tangent sigmoid and linear).

The proposed algorithm includes multiple subtasks for validation of the ANN model developed:

- testing points used in model development,
- testing new points,
- sensitivity analysis of the model.

Here a certain contradiction in the selection of testing points also exists. From one side the validation is thoroughgoing if a large number of data points are used for testing. From the other side, in most cases it is not reasonable to take a big number of data points for testing, but instead include most data for model development. Some critical applications can be considered as exceptions.

It is well known that the response surface corresponding to the ANN model may not contain the exact values of the objective function determined from tests. The ANN model validation is finalised by performing sensitivity analysis. The output vector Y as a function of the input vector X can be computed for the ANN with one hidden layer as

$$Y = G_2(W_2 G_1(W_1 X + \Theta_1) + \Theta_2), \quad (3.29)$$

where W_1, W_2 and Θ_1, Θ_2 stand for weight matrices and bias vectors, respectively. In Eq. (3.29) G_1 and G_2 stand for the transfer functions in the hidden and output layers, respectively. The sensitivity matrix S can be computed as a gradient of the output vector Y as

$$S = \frac{\partial Y}{\partial X} = \frac{\partial G_2}{\partial Z_2} W_2 \frac{\partial G_1}{\partial Z_1} W_1, \quad (3.30)$$

In Eq. (3.30)

$$Z_1 = W_1 X + \Theta_1, \quad Z_2 = W_2 G_1(Z_1) + \Theta_2. \quad (3.31)$$

By performing sensitivity analysis the robustness of the solution has been confirmed, the computed values of the sensitivities with respect to design variables remain moderate. The ANN model developed allows prediction of the values of the temperature, current and vibrations for desired input dataset remaining in a predefined design space. The obtained results can be applied for determining the working regimes of the machine (equipment), forecasting wear of machine components and their proper lifetime.

3.5 Conclusions of Chapter 3

The artificial neural network based mathematical model has been composed for estimating the values of the vibrations, current and temperature affecting the working regimes and tool life.

First, the ANOVA analysis was performed on the experimental data with aim to estimate the influence of the cutting speed, feed rate and cutting depth on vibrations, temperature and current. The analysis was carried out at level of confidence of 95% (i.e. significance of 5%). Table 3.3 shows the computed p-values for all factors considered.

Table 3.3 ANOVA analysis, the p-values.

Factor	**Current**	**Temperature**	**Vibration x-axis**	**Vibration y-axis**	**Vibration z-axis**
Cutting speed	0.0046	0.0000	0.0244	0.0032	0.0000
Feed rate	0.0000	0.0000	0.0369	0.0574	0.0000
Cutting depth	0.0003	0.0001	0.4049	0.9061	0.0083

It can be observed from Table 3.3 that all factors are significant for current, temperature and z-component of the vibrations, since their p-value is less than 0.05. The cutting depth is insignificant for the x and y component of the vibrations and the feed rate is insignificant for the y component of the vibrations.

Fig. 3.4 shows performance plot of the MATLAB based ANN model for temperature: errors vs. training epochs.

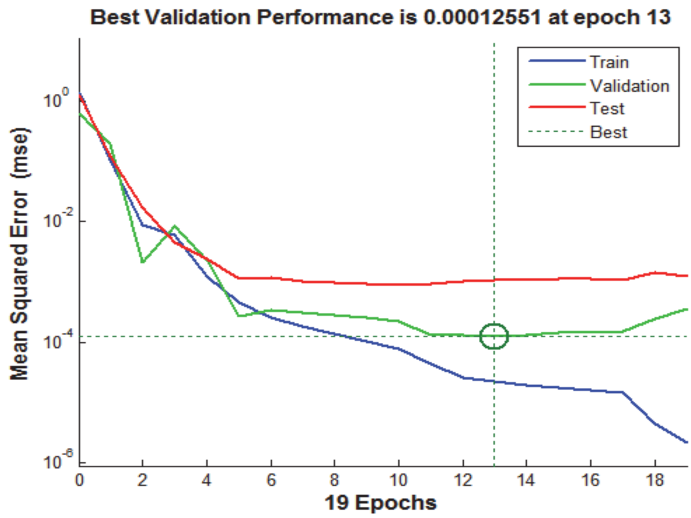

Figure 3.4 Performance plot.

In the second stage the discrete tool/component life prediction model was developed. In Fig. 3.5 is shown dependence of the tool life on cutting speed and feed.

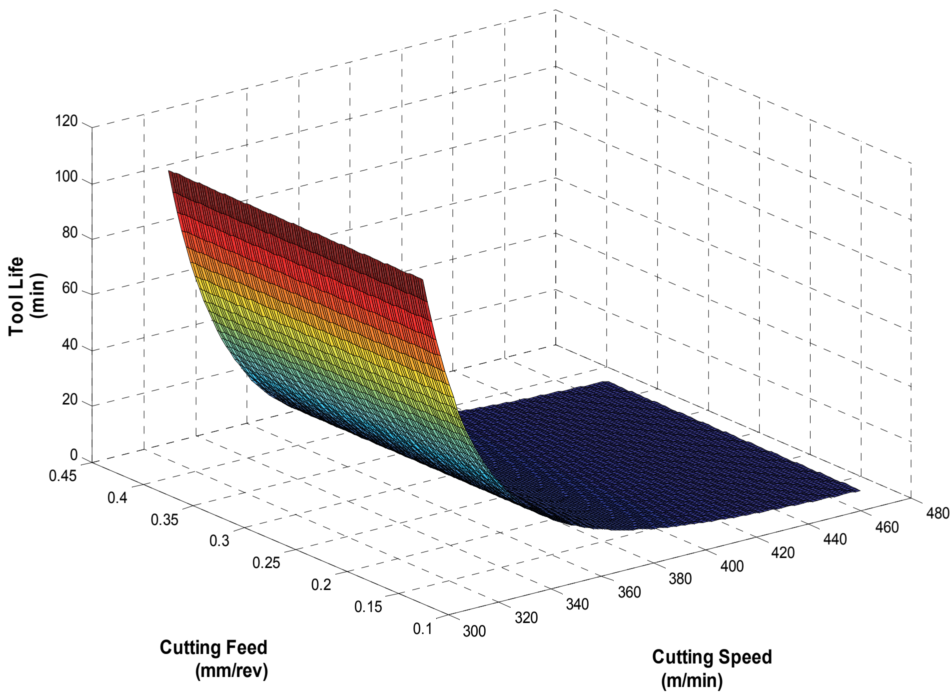

Figure 3.5 Tool life dependence on cutting speed and feed.

It can be seen from Fig. 3.5 that the tool life is increasing with decreasing values of the cutting speed (exponential relation) and cutting feed (less distinguishable on Fig. 3.5 due lower values of the feed and its exponent in model). The function $L_{pp}(S^0_{cut\_speed}, f^0_{feed\_rate}, D^0_{cut\_depth})$ is implemented as Taylor extended model Eq. (3.14) in order to compose Fig. 3.5. In more general case the regression, ANN, etc. techniques can be applied for modelling function L_{pp}. The extended Taylor model constants are determined by applying linear regression to experimental data (first the relation Eq. (3.14) is converted to linear form by applying logarithms). When function L_{pp} is determined the process parameters coefficient L_{proc_par} can be evaluated using Eq. (3.13). Next, the total remaining life expectancy time can be computed from Eq. (3.22) taking account the effect of bad/extreme working regimes.

Main differences of the current approach from widely used ‘classical’ models [Li, 2012] can be outlined as:

- Current approach is based on real time monitoring data (measured values of the vibrations, temperature, current), thus as a rule the effect of particular materials, tools, etc. used are more accurately covered.
- Most of the models allow to predict tool life as a whole under certain exploitation conditions (values of process parameters, working regimes, etc.). The proposed concept and model allows additionally to estimate remaining tool life also for partially used tool if the exploitation conditions during used and forward time are known.
- The widely used simple models are commonly deterministic. The proposed model includes uncertainty term.
- The widely used simple models commonly consider the effect of the processing parameters only for estimating tool/component life expectancy (like the Taylor extended model uses cutting speed, feed rate and cutting depth). In the current approach the effect of working regimes covering extreme exploitation conditions which may be caused by some defect, damage or breakage of machine components and also external factors, are additionally considered.
- The widely used simple models are commonly continuous (see Taylor, extended Taylor, etc.). The current approach includes discrete variables.
- Current approach needs more input data for covering a wider range (not only normal/standard exploitation conditions).
- In the cases when the ANN model proposed covers normal and extreme exploitation conditions (working regimes) the tool life prediction can be performed without real time monitoring. The working regimes can be determined based on the values of the processing parameters (cutting speed, feed rate, cutting depth) and ANN model.

The system design and predictive model results demonstrate the usefulness of the proposed PMS.

4 CONCLUSIONS

Based on the objectives and activities of the thesis the general conclusions of the work is as follows:

1) Production monitoring system concept with main modules and prediction functionality was presented.
2) Based on the concept a modular and expandable wireless production monitoring system was built and tested to collect data for predictive modelling and a visual module to visualise collected data (e.g. availability, KPI, sensor data). Modular design allows adjustments of the system based on requirements. Developments of GUI that has different levels of data visualisation were presented. Production monitoring system was developed and tested based on open source hardware and software. Low investments to implement the proposed PMS simplifies the introduction of such systems to SMEs.
3) The two stage tool life expectancy model based on derivation of discrete analytical tool life prediction model and artificial neural networks model for determining dependence of the vibrations, temperature and current on process parameters (cutting speed, feed rate and cutting depth), was developed and tested. The proposed model allows normal and extreme working conditions to be covered.

Novelty of the study:
Novel solutions are proposed and presented in the theses:

- New PMS development with extendable functionality for monitoring manufacturing processes of machinery and production lines for SMEs;
- The predictive model for estimating remaining life expectancy time of the tool/component. This model considers effect of process parameters and working regimes (covering extreme conditions) on tool life;
- The proposed concept and predictive model allows to estimate the remaining tool life also for partially used tool based on values of processing parameters, working regimes, etc. during used and forward exploitation time.
- Concept of PMS with predictive functionality based on open-source hardware and software.

Further research:
Development of advanced PMS is a continuous process and with regards to diversification there is definitely a need for more case studies and different developments.
Results obtained in the current study can be extended in future works. For example:

- The web interface should be further developed to introduce more different levels of data presentations. For higher management level (e.g. CEO) clear key performance indicators should be chosen.
- Data archiving, security and synchronisation between different servers should be further investigated.
- Exploitation of monitoring data collected and analysed by PMS could be considered for discrete event simulation in Virtual Factory approaches [Kádár *et al*., 2010; Terkaj *et al*., 2015].
- Integration and data fusion between enterprise and control systems should be developed. Here the use of semantic web technologies to support the interoperability could be considered [Kádár *et al*., 2013].
- The proposed predictive model for tool life estimation can be improved for covering better stochastic behaviour (currently probabilistic behaviour is included, but only for working regimes).

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ABSTRACT

Development and Optimisation of Production Monitoring System

With the growing complexity of production operations the scale and scope of the data to be monitored and controlled simultaneously increases. It requires the implementation of advanced automatic production monitoring systems.

Quick and reliable automatic data collection and analysis from the shop floor is one of the applications that has been in focus for many production companies and research institutions.

The main objective of the current research is to analyse and develop a production monitoring system that enables one to automatically acquire and analyse relevant data from the workshop. The PhD thesis is based on the published articles.

Research covers development of the concept and prototype of the wireless system for data collection and analysis in the workshop, focusing on small and medium sized production companies. The aim is to develop an affordable, effective and highly configurable system based on open-source technologies. Together with the proposed multi-level graphical user interface it will support producers to meet set targets.

The concept of a production monitoring system with predictive functionality was described and a prototype made. As each production system has its own specifics with a huge variety of possible modifications, the production monitoring system should be flexible for modifications. The trends are: web-based architecture, re-configurability, near real time performance, open-hardware and software, predictive functionality, wireless connectivity, supported by cloud computing.

Based on the system concept, the predictive modelling was performed that consists of the following basic steps as

- data analysis, development of mathematical model for describing the dependence of the current, temperature and vibrations on processing parameters (cutting speed, cutting depth and feed rate),
- development of an analytical tool life prediction model covering the effect of the process parameters and working regimes.

The tool life prediction model developed is based on the use of near real time monitoring data captured by the production monitoring system.

Keywords: production monitoring system, artificial neural network, predictive functionality, machinery or production line state monitoring, component or tool life prediction model.

KOKKUVÕTE

Tootmise monitooringu süsteemi arendus ja optimeerimine

Tootmisoperatsioonide ja tehnoloogiate kasvav keerukus suurendab reaalajas jälgitavate ja kontrollitavate andmete hulka, mis kasvatab investeeringute vajadust nii riist- kui tarkvarasse. See omakorda tõstab päevakorda vajaduse automaatsete tootmisliinide ja seadmete monitooringu süsteemide juurutamiseks.

Kiire ja usaldusväärsete tootmiskeskkonna andmete kogumine ning sellele järgnev andmete töötlemine ja analüüs on kriitilise tähtsusega nii tootmisettevõtetele kui ka teadusasutustele.

Antud uurimistöö peamine eesmärk on analüüsida ja arendada tootmise monitooringu süsteemi, mis võimaldab automaatselt koguda ja analüüsida andmeid nii üksikutelt seadmetelt kui ka erinevatelt tootmisliinidelt.

Käesolev doktoritöö baseerub avaldatud teadusartiklitel. Töö sisaldab traadita tootmise monitooringu süsteemi kontseptisooni väljatöötamist ning prototüübi arendust ja testimist, keskendudes väikese ja keskmise suurusega tootmisettevõtete vajaduste rahuldamisele.

Uurimistöö põhiline eesmärk on arendada väikese maksumusega, effektiivne ja lihtsalt konfigureeritav tootmise monitooringu süsteem, mis põhineb avatud (lähtekoodiga) tehnoloogiatel. Koos mitmetasandilise graafilise kasutajaliidesega võimaldab arendatud süsteem suurendada tootmise läbilaskevõimet, optimeerida sisemisi protsesse, vähendada kadusid ning tootmisele kuluvat aega.
Süsteem on paindlik ja võimaldab jooksvalt laiendada funktionaalsust, vastavalt hetke vajadustele. Arendamisel kasutati erinevaid trende: veebi-põhine arhitektuur, seadmete traadita ühenduvus, avatud riist- ja tarkvara, ennustav funktsionaalsus, paindlikkus, pilvandmetöötlus.

Lähtudes tootmise monitooringu süsteemi kontseptsioonist, arendati uurimistöös välja ka prognoosimismudel tööriista või seadme komponendi eluea prognoosimiseks. Arendatud mudel koosneb järgnevatest etappidest:

- Andmete analüüs ja matemaatilise mudeli arendamine, mis kirjeldab temperatuuri, voolu ja vibratsiooni sõltuvust töötlusparameetritest (lõikekiirus, lõikesügavus ja ettenihe).
- Tööriista või komponendi eluea prognoosimismudel, mis põhineb kogutud ja analüüsitud andmetel.

Märksõnad: tootmise monitooringu süsteem, tehisnärvivõrk, ennustav funktsionaalsus, seadme või tootmisliini seisundi jälgimine, tööriista või komponendi eluea prognoosimismudel.

APPENDICES

PAPER I

Snatkin, A., Karjust, K., Eiskop, T. (2012). Real time production monitoring system in SME. In: *Proceedings of the 8th International Conference of DAAAM Baltic Industrial Engineering*, Tallinn, Estonia, 573-578.

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REAL TIME PRODUCTION MONITORING SYSTEM IN SME

Snatkin, A.; Karjust, K.; Eiskop, T.

Abstract: *The main objective of the current study is to analyse real time production monitoring systems (PMS) and to offer better solutions for small and medium sized production companies. PMS is the alternative to manual data collection and should capture most of the required production data without human intervention.*
Practical part of the study is focused on selection of suitable PMS, its adaption and mapping manufacturing process (determining key factors, etc.).
Key words: production monitoring system, remote monitoring, real time information, manufacturing execution system.

1. INTRODUCTION

The objective of the paper is to give an overview of advantages and possible drawbacks of a PMS before starting to implement such system in a specific SME. SMEs are more flexible comparing to larger companies and can faster implement a new way of doing business. Also the result of changes can be seen earlier that simplifies the research.
In a fiercely competitive market, companies cannot afford the waste of time and resources to perform work that can be done in a better and faster way with advanced solutions. One of the advanced solutions can be a real time PMS. It is a production tool that collects and distributes necessary data when various events occur in a shop floor. The main aim of a PMS is to prevent small disturbances having large effects. In this way a PMS will decrease the number of unscheduled production stops, improve cost-efficiency and simplify the production planning.

2. PRODUCTION MONITORING SYSTEM

The task of a PMS is to collect and distribute real time data of events on the shop floor. This data must be understandable and useful for decision making. Monitored data should help the production team to respond timely on the events that may affect the desired result.
Such system should also alarm and inform respective department concerning all recognized faults.
PMS is not just display boards that show production data, it also has a reporting and administration module, where stored data can be analysed to find trends, estimations and projections for easier decision making and production planning.
Proactively detected faults will decrease wasted time and improve overall equipment effectiveness.

2.1 Manufacturing Execution System

Production monitoring and machine data collection is one of a Manufacturing Execution System's (MES) functions.
Historically, each software editor had their own definition of an MES which was generally based on the capacities of their own tools or on the expectations of their customers [1].
Several of the major automation providers offer now MES solutions, including Emerson, GE, Honeywell, Invensys, Rockwell and Siemens.
MES integrates separate data collection systems. It is like a linkage between the

shop floor and office. It should solve the problems of the lack of integration between the Enterprise Resource Planning (ERP) systems and the control systems on the plant floor.
MES position in the factory automation system can be described in different ways. To understand on what enterprise automation level it is positioned, a pyramid diagram can be used. Please see Figure 1.

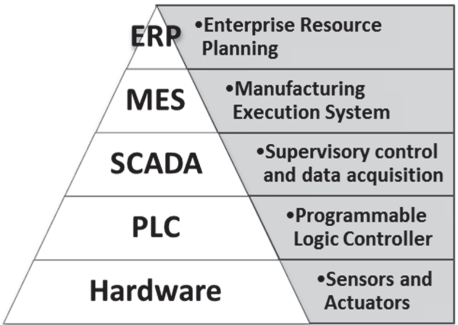

Fig. 1. Automation Pyramid [2].

The standard of International Society of Automation ISA S 95 best describes the architecture of a MES into more detail, covering how to distribute functionality and what information to exchange internally as well as externally.

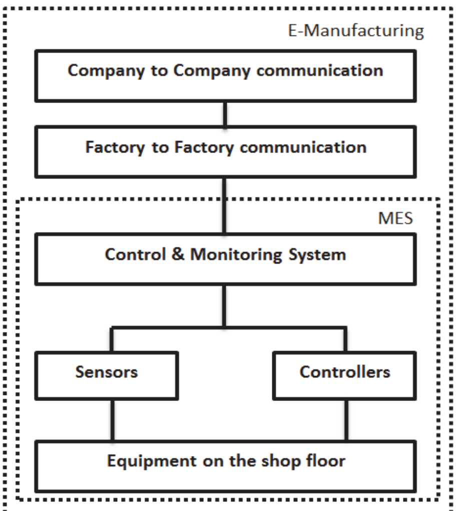

Fig. 2. The diagram of the e-manufacturing and MES.

MES is overlapping with the Product Lifecycle Management (PLM) system in the production phase [2,3,4]. It means that changes made by MES during the production (machine adjustment, tolerance change etc.) may have influence on the PLM workflow (changes in drawings and CAM).
From e-manufacturing point of view, a MES is the lower level of factory automation and communication systems [5]. Please see Figure 2.

2.2 Real time information handling and classification

The idea of a real time PMS is not to give some information simultaneously as the event occurred, but provide the production team, as fast as possible, with the accurate and meaningful data. But it should be enough time to respond timely on these events.
It will always take some time (seconds, minutes or even hours) to analyse monitored data and respond on it. And the goal is to try to decrease this time.
Real time production monitoring information can be classified into two main groups. One group is related to the status of resources and another one to the status of jobs. Information on actual or potential disruptions may relate to resources or jobs. Machine breakdowns, material or tool shortages and longer-than-expected processing times give resource problems. Job related disturbances arising from planning systems and customers include changes in priority, reassignments of jobs to orders and the emergence of new jobs. Quality problems may relate to both resources and jobs [6].
Classification of real time information helps to understand how the desired PMS should be structured.
The first step of real time data in the monitoring process is detection. Data can be detected by sensors, operators, barcode scanner etc. Understanding the detection process will lead to effective use of real time data capture devices, and removal of

unnecessary and useless devices. Then data should be classified and identified. For example, transferred to respective department or handled automatically. And the last step is diagnosis and analysis [6].

There is no reason to store all collected data in the database. Good decision will decrease running costs and improve performance of the database.

3. CONCEPT OF A PRODUCTION MONITORING SYSTEM

Production data collected on the shop floor may be incorrect, mostly due to human intervention or improper production monitoring system. The human factor is more common in this case. That is why a PMS should capture most of the required data without human intervention.

When an unscheduled outage does happen, time is spent notifying support resources that a problem has occurred, time is spent for the support resource to respond to the issue, time is spent troubleshooting and finally time is spent to resolve the problem. But predictive nature of continuous remote monitoring more often avoids unscheduled outages by addressing the issues before they affect machine operation and product quality [7].

The benefit of installing an efficient real time PMS is the immediate access to all required production related information by the relevant personnel. And it should be enough data to clearly identify the reasons of production stops, time loss etc. At the same time, presenting too much information can confuse or even distract operators.

The most important requirements of any PMS are that the system is economical, accurate and easy to set up on a production line. And it has to be capable of providing straightforward connectivity to switches, sensors, PLC outputs and other common industrial equipment. If the true production data can be automatically captured and presented in a simple, understandable way to the operators, they will become a more integral part of the improvement process [8].

Relatively simpler systems may have greater potential for real-time control [9].

An effective production monitoring system should be at least comprised of the four elements: collection, display, analysis and data storage (see Figure 4).

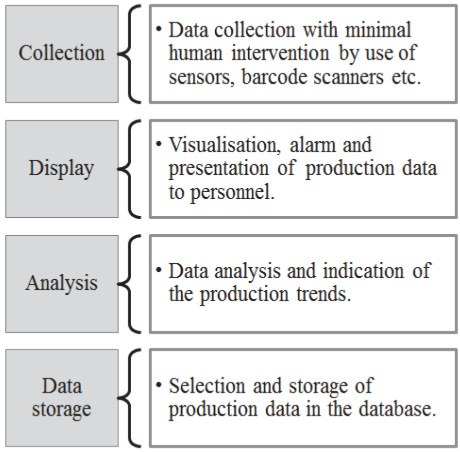

Fig. 4. PMS modules.

Alarm system is also one of the basic capabilities of a PMS. Fault annunciation should be properly understood by the personnel to act in a timely manner. And an advanced PMS should provide the possibility to review historical site alarm activity.

Visualisation of data can be made through displays, andon boards and mobile solutions, like smart-phones etc.

4. PMS INTEGARION ON THE SHOP FLOOR

Because of the high cost of deployment of automated manufacturing systems, machines are not integrated on most shop floors [10]. Production industry still gathers most of the data in the shop floor through manual inputs.

Despite the fact that number of automation providers offer MES solutions, such systems are mostly monolithic, insuffici-ently configurable, and difficult to modify.

Installing such software and integrating it with current systems is found to be a challenging and costly undertaking [11].
Localized solutions can be more affordable and even more strengthen the advantage of an automated production monitoring. Especially during the economic recession, companies are more precisely weigh the pros and cons of investing money in a new production system. And faster return on investments can be the decisive moment when choosing a production monitoring system, though alternative MES systems can offer a wide range of additional functions.
When calculating costs of a PMS, not only software and hardware investments should be calculated. Possible consultation and support costs must be taken into account. If system is developed and integrated in cooperation with the production team, these costs can be decreased.
In case of modern manufacturing equipment, a monitoring system is assumed to be a part of the machinery. Installing wireless sensors (so called “smart dust”) on machinery can be one of the solutions. Before that, models should be developed that reflect the correlation between the state of the machine and the monitored parameter. All these will enable the detection of failures and critical modes of operation. Installing a monitoring system, based on wireless sensor nodes, is relatively cheap and it can be fitted to both old and modern manufacturing equipment [12]. Wireless sensors eliminate the cost of cables that also simplifies the install.
In real life wireless monitoring is used infrequently in shop floors [13].

5. TRENDS

The trends of PMS solutions can be summarized as follows:

- Standardized plug & play connectivity
- Real time performance
- Web-based architecture
- Scalability and re-configurability

It is evident that the amount of information collected from control systems increases tremendously with the degree of increased automation on the shop floor. Manufacturing systems grow because of the need for more complex processes to meet the needs of increased product functionality [1]. It means that PMS has to be connected to more equipment and process more data at the same time.
In addition to these trends, there is future direction to self-learning and decision making system that maximally eliminate human intervention.
General trend is to use PMS for improvement of the production processes by applying: statistical process control, mathematical modelling and optimization of the production process [14-18].

7. CASE STUDY

The monitoring systems are designed for four workbenches in Tallinn University of Technology (TUT) and for two work lines in private company JELD-WEN Estonia. The data collection and display modules are completed, but the development of the analysis module is in progress.
Measuring devices will be assembled on a controlled machinery to conduct measurements. It will provide early warnings of machine degradation or impeding accident. The characteristics chosen for monitoring and the measurement equipment selected are outlined in Tables 1-5.

Sensor	Measurement
Optical / Hall effect sensor	Spindle speed
Accelerometer / piezoelectric sensor	Spindle vibration
Infrared temperature sensor	Bearing temperature
Clip-on ammeter	Current
Magnet / Hall effect sensor	Carriage mechanism position

Table 1. Metalworking lathes, 1K62B and 16A20 (TUT)

Sensor	Measurement
Optical / Hall effect sensor	Spindle speed
Accelerometer / piezoelectric sensor	Spindle vibration
Infrared temperature sensor	Belt friction point temperature
Clip-on ammeter	Current, load

Table 2. Milling machine DYNA MECH. EM3116 (TUT)

Sensor	Measurement
Temperature sensor	Coolant temperature
Accelerometer / piezoelectric sensor	Working table vibration
Optical / magnet sensor	Wire feed speed and brake
Conductivity meter	Water (coolant) salinity
Clip-on ammeter	Current, load

Table 3. Wire-cut machine AGIE AC 50/120H (TUT)

Thus, in TUT the milling, wire-cut and lathe machines are set up for monitoring.

Sensor	Measurement
Rotary encoder	Line speed
Optical sensor	Material availability on the line

Table 4. Output of planer line Weinig 141 (JELD-WEN Estonia)

Sensor	Measurement
Optical sensor	Count of material from the in-feed
Optical sensor	Count of material reaching machine

Table 5. Input of the painting line Makor (JELD-WEN Estonia)

In the private company JELD-WEN Estonia the output of planer line and input of the painting line are designed and set up for monitoring (not workbenches).

8. FURTHER RESEARCH

Each production SME has differences in manufacturing processes, equipment, priorities and capital resources. That is why such questions still need to be answered:

- Which data should be collected first?
- Which data have to be saved and for how long in the PMS database?
- Is it possible to design a “plug and play” PMS solution that is suitable for most of the production SMEs?
- What is the easiest way to connect different data formats and communication interfaces?
- How to visualise the production data to make it clear to all personnel?

9. CONCLUSION

The real time PMS systems designed for TUT and JELD-WEN Estonia enables to continuously acquire data from the shop floor with regard to efficiency, malfunctions and productivity. This leads to improved production capacity and cost-efficiency, helps to achieve desired production goals. Development of the data analysis module has been foreseen as next task in improvement of PMS system.

10. ACKNOWLEDGEMENTS

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PAPER II

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Real time production monitoring system in SME

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Abstract. Real time production monitoring systems (PMSs) is an alternative to manual data collection and captures most of the required production data without human intervention. The general objective of the current study is to analyse PMSs and to offer particular solutions for small and medium sized enterprises (SMEs). The subtasks to be solved in the case of each particular PMS include determining relevant parameters, designing PMS and development of the data analysis and prognosis model for short term and long term planning. The selection of suitable PMS components and relevant parameters and the development of lathe cutting unit measuring system are described in the case study. Defendec Inc. and National Instruments Corporation wireless components were adopted to implement a part of the PMS.

Key words: production monitoring, remote monitoring, real time information, manufacturing execution system, wireless sensor network, maintenance planning.

1. INTRODUCTION

The objective of the paper is to give an overview of the advantages and possible drawbacks of a PMS before starting to implement such a system in a specific manufacturing SME. SMEs are more flexible comparing to larger companies and can faster implement a new way of doing business. Also the result of changes can be seen earlier, which simplifies the research and offers quicker feedback.

Nowadays, in an open and competitive market, companies cannot afford the waste of time and resources to perform work that can be done in a better and faster way with advanced solutions. One of the advanced solutions can be the real time PMS. It is a production tool that collects and distributes necessary data when various events occur in the shop floor. The main aim of a PMS is to prevent small disturbances having large effects. In this way, a PMS will decrease the number of unscheduled production stops, improve cost-efficiency and simplify the production planning.

The task of a PMS is to collect and distribute real time data of events in the shop floor. This data must be understandable and useful for decision making. Monitored data should help the production team to respond timely to the events that may affect the desired result. Such system should also alarm and inform the respective department concerning all recognized faults.

PMS is not just display boards that show production data, it also has a reporting and administration module, where stored data can be analysed to find trends, estimations and projections for knowledge-based decision making and production planning. Proactively detected faults will decrease wasted time and improve overall equipment effectiveness.

Production monitoring and machine data collection is one of the manufacturing execution systems (MES) functions. Historically, each software editor had its own definition of the MES, which was generally based on the capacities of their own tools or on the expectations of their customers [1].

Several of the major automation providers offer now MES solutions, including Emerson, GE, Honeywell, Invensys, Rockwell and Siemens. MES integrates separate data collection systems. It is like a linkage between the shop floor and office. It should solve the problems of the lack of integration between the enterprise resource planning (ERP) systems and the control systems on the plant floor.

MES position in the factory automation system can be described in different ways. To understand on what enterprise automation level it is positioned, a pyramid diagram can be used (Fig. 1).

The standard of the International Society of Automation ISA S 95 describes the architecture of a MES in greater detail, explaining how to distribute functionality and what information to exchange internally as well as externally. MES is overlapping with the product lifecycle management (PLM) system in the production phase [2–4]. It means that changes made by MES during the production (machine adjustment, tolerance change etc.) may have influence on the

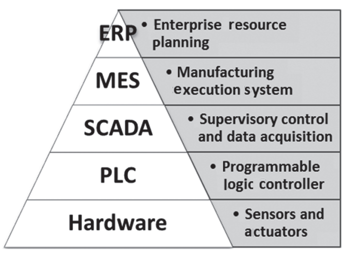

Fig. 1. Automation pyramid [2].

PLM workflow (changes in drawings and CAM). From the e-manufacturing point of view, a MES is the lower level of factory automation and communication systems [5].

The idea of a real time PMS is not to give some information simultaneously with the event but to provide the production team, as fast as possible, with the accurate and meaningful data. But there should be enough time to respond timely on these events. It will always take some time (seconds, minutes or even hours) to analyse monitored data and to respond to it. And the goal is to try to decrease this time.

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Classification of real time information helps to understand how the desired PMS should be structured. The first step of real time data in the monitoring process is detection. Data can be detected by sensors, operators, barcode scanner, etc. Understanding the detection process will lead to effective use of real time data capture devices and to the removal of unnecessary and useless devices. Then data should be classified and identified; for example, transferred to respective department or handled automatically. The last step is diagnosis and analysis [6].

It is not reasonable to store all collected data (every single measurement) in a database. If the measurements are taken with high frequency (e.g. vibration) by using wireless sensor network (WSN), it is recommended to process an original data already in the WSN node, before sending the analysed data to the database. In this manner, WSN node energy can be saved, radio frequency channel can be held free longer time and database can be held more compact.

The trends of PMS solutions can be summarized as follows:

- Standardized plug & play connectivity;
- Real time performance;
- Wireless communication;
- Web-based architecture;
- Scalability and re-configurability.

It is evident that the amount of information, collected from control systems, increases tremendously with the degree of increased automation on the shop floor. Manufacturing systems grow because of the need for more complex processes to meet the needs of increased product functionality [1]. It means that PMS has to be connected to more equipment and it processes more data at the same time. In addition to these trends, there is a trend to self-learning decision making systems that maximally try to eliminate human intervention. General trend is to use PMS for improvement of the production processes by applying statistical process control, mathematical modelling and optimization of the production process [7–11].

2. CONCEPT OF A PRODUCTION MONITORING SYSTEM

Production data, collected on the shop floor, may be incorrect, mostly due to human intervention or the improper production monitoring system. The human factor is more important in this case. That is why a PMS should capture most of the required data without human intervention.

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An effective production monitoring system should comprise at least five elements: collection, display, analysis, prognoses and data storage (Fig. 2). In the current development model, the prognoses module is added, which gives to the company additional flexibility that beside the short term planning (PMS system will automatically alarm, when some critical determined parameters reach the limit) we can make also long term planning to forecast future defects and tool life time. Using that information and prognoses module we can avoid the actual defects and plan the maintenance so that we will make the change of the wearing before it actually breaks.

Alarm system is also one of the basic capabilities of a PMS. Fault announcement should be properly understood by the personnel to act timely. An advanced PMS should provide the possibility to review the history of the alarms. Visualization of data can be made through displays, andon boards and mobile solutions, like smart-phones, etc.

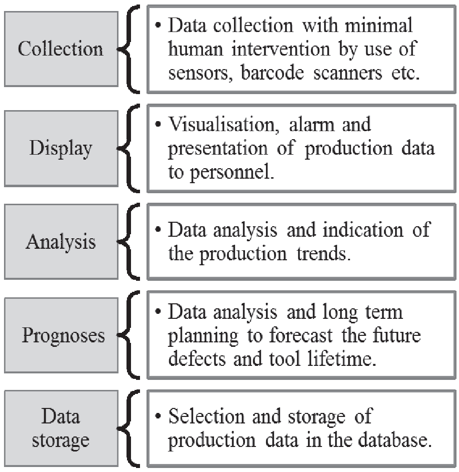

Fig. 2. PMS modules.

3. PMS INTEGRATION ON THE SHOP FLOOR

Because of the high cost of deployment of automated manufacturing systems, machines are not integrated on most shop floors [15]. Production industry still gathers most of the data on the shop floor through manual inputs.

Despite the fact that a number of automation providers offer MES solutions, such systems are mostly monolithic, insufficiently configurable, and difficult to modify. Installing such software and integrating it with current systems is found to be a challenging and costly undertaking [16].

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When calculating costs of a PMS, not only software and hardware investments should be calculated. Possible consultation and support costs must be taken into account. If a system is developed and integrated in cooperation with the production team, these costs can be decreased.

In case of modern manufacturing equipment, a monitoring system is assumed to be a part of the machinery. Installing wireless sensors (so-called “smart dust”) on machinery can be one of the solutions. Before that, models should be developed that reflect the correlation between the state of the machine and the monitored parameter. All these will enable the detection of failures and critical modes of operation. Installing a monitoring system, based on wireless sensor nodes, is relatively cheap and it can be fitted to both old and modern manufacturing equipment [[17]]. Wireless sensors eliminate the cost of cables that also simplifies the installation. In real life wireless monitoring is used infrequently on shop floors [[18]].

4. A CASE STUDY

Monitoring systems have been designed for four machine tools at the Tallinn University of Technology (TUT) and for wood product manufacturing line in the private company JELD-WEN Eesti AS. The data collection and display modules are completed, but the development of the analysis module is in progress.

4.1. Monitoring system design based on sensors selection

Measuring devices will be assembled on a controlled machinery. That will provide early warnings of machine degradation or impeding accident and will give input parameters to the prognoses module. The characteristics, chosen for monitoring and the measurement equipment, selected at TUT, are outlined in Tables 1–3, and at the private company JELD-WEN Eesti AS in Tables 4–5.

Table 1. Metal working lathes, 1K62B and 16A20

Need to know	Measuring	Sensor type
Machine tool is working/not working and with what load	Current in main cable	Clip-on ammeter
Spindle rotating speed	No of revolutions in time unit	Hall effect sensor
Work piece diameter	Distance from sensor to work piece	Optical sensor
Stability of spindle	Vibration in spindle	Acceleration/piezoelectric sensor
If tool is dangerously close to spindle	Carriage position	Magnet/Hall effect sensor
Bearing wearing rate	Bearing surface temperature	Thermocouple

Table 2. Milling machine DYNA MECH. EM3116

Need to know	Measuring	Sensor type
Machine tool is working/not working and in what load	Current in main cable	Clip-on ammeter
Spindle rotating speed	No of revolutions in time unit	Hall effect sensor
Stability of spindle	Vibration in spindle	Acceleration/piezoelectric sensor
Spindle engine pulley temperature	Belt friction point temperature	IR temperature sensor

Table 3. Wire-cut machine AGIE AC 50/120H

Need to know	Measuring	Sensor type
Machine tool is working/not working and in what load	Current in main cable	Clip-on ammeter
If coolant temperature is too high	Coolant temperature in storage reservoir	Temperature sensor
Coolant salt concentration	Water (coolant) salinity	Ultrasonic sensor/conductivity meter
Work table stability	Vibration in work table	Acceleration/piezoelectric sensor
Wire feed rate and breaks	Roller No. of revolutions in time unit	Hall effect sensor

Table 4. Planer line Weinig 141

Need to know	Measuring	Sensor type
Input material quality, is it suitable or not	Material geometry	Optical sensor
Line speed and total length of material processed	Line speed	Rotary encoder
Stoppages, time machine is waiting for material	Material availability on the line	Optical sensor

Table 5. Painting line Makor

Need to know	Measuring	Sensor type
Total number of products feed to the line	Count of material from the in-feed	Optical sensor
Number of high quality products that need no additional repairs	Count of material reaching machine	Optical sensor

Thus, at TUT the milling, wire-cut and lathe machines are set up for monitoring.

In metal working lathe, cutting tool condition monitoring is highly important as the tool condition changes fast and it has direct impact to machining quality. Cutting tool producers give life expectancy for a tool from 15 to 90 min, depending on working parameters (mostly on cutting speed). Mitsubishi Materials give life expectancy for their steel (reference material: carbon steel, alloy steel 180HB) processing turning tools 15 min, if the cutting speed is 320 m/min. Decreasing the speed about 40% (depending on tool and work piece material), the tool life expectancy grows to 90 min.

Spindle rotating speed and work piece diameter are important parameters as they determine the cutting speed. Cutting speed can be calculated as

$$V_c = \frac{\pi D n}{1000}, \qquad (1)$$

where V_c is cutting speed (m/min), D is work piece diameter (mm) and n is spindle speed (min^{-1}).

In the company JELD-WEN Eesti AS the input and output of the planer line and input of the painting line are designed and set up for monitoring (not machine tools). Currently four optical sensors and one rotary encoder are installed. The evaluation of the input material quality is performed automatically from measurements up to the selection of material for different products.

In this work, we focus on the metalworking lathe 16A20. Data collection and analysis module for other equipment is in progress.

4.2. WSNs components comparison

Two wireless sensor networks WSNs were adapted to metalworking lathe 16A20 to implement PMS. For these WSNs, different hardware and software were used, to compare their pros and cons. Main parameters of the adapted WSNs components and nodes are shown in Table 6.

The first WSN was designed to monitor the lathe front bearing temperature dynamics. The lathe front bearing temperature was measured at two points with J-type thermocouples. National Instrument (NI) WSN-3212 4ch 24 bit Thermocouple Input Node was used for real measurements. The first thermocouple was placed in contact with the spindle front bearing housing from inside the gearbox; the second thermocouple was placed in contact with the spindle front bearing flanged housing between gearbox and spindle (Fig. 3).

The data acquisition interval was 1 s and all the results were saved in real time in PostgreSQL database table with the following field layout:

1) timestamp – holding time of measurement,
2) sequence – measurement sequence No in the current test,
3) nodeID – ID of the measurement node (for saving measuring results of different nodes to one table),
4) value1 – actual measured value (the temperature of the first thermocouple),
5) value2 – actual measured value (the temperature of the second thermocouple).

Sample set of measurement values saved to PostgreSQL database are presented in Table 7. For further analysis, data from the database can be presented graphically. In Fig. 4, sample temperature dynamics is presented, using collected

Table 6. WSNs components used in monitoring

Type of components used	Bearing temperature monitoring	Lathe utilization (spindle speed) monitoring
Sensor	J-type thermocouples	Hall effect sensor
Node	NI WSN-3212	Defendec node
Node is programmable	No	Yes
Node maximum sampling rate	1 sample/s	More than 2000 samples/s
Gateway	NI WSN-9791	Defendec gateway
Database	RDBMS PostgreSQL	MySQL

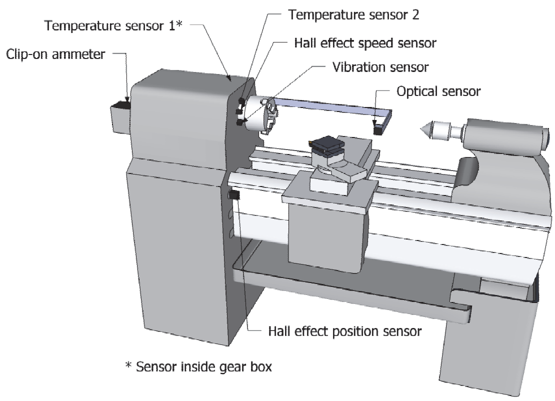

Fig. 3. Lathe cutting unit measuring system.

Table 7. Sample set of measurement values from the PostgreSQL database

Timestamp	Sequence	Node	Value1	Value2
15.10.12 10:55:06	0	2	29.048	30.107
15.10.12 10:55:07	1	2	29.032	30.103
15.10.12 10:55:08	2	2	29.015	30.098
15.10.12 10:55:09	3	2	28.615	30.014
15.10.12 10:55:10	4	2	28.492	29.988
15.10.12 10:55:11	5	2	28.299	29.981

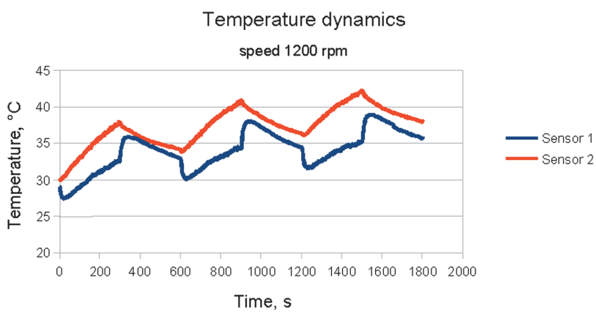

Fig. 4. Sample temperature dynamics graphic.

measurement data from the database. Temperature dynamics is collected by experiment, where 300 s free spindle running and 300 s spindle standstill were in turn three times.

The second WSN was designed to monitor the lathe utilization information. Utilization was determined by measuring the speed of the spindle. It was presumed that rotating spindle means that the machine tool is utilized. Hall effect sensor was placed between the gearbox and the spindle (Fig. 3) in the position, where spindle bolts were close enough to the sensor to influence it. Three spindle bolts were influencing the sensor, when they passed the sensor. It means, there were three times more sensing points than spindle turns. Defendec programmable node counted signals in one second and divided them by three to determine spindle speed. The node was programmed to send data, if the spindle speed was changed more than 10 rpm.

Defendec and NI hardware were used in the monitoring application. NI hardware and software LabView are easier to use than the Defendec node, as NI equipment is preinstalled and the programming environment is graphical. It is possible to graphically illustrate measurement results without using the database. It gives the advantage to create simple monitoring applications with illustrative graphics faster, but in a more advanced system, it has programming limitations. Current NI node was not programmable, but it is available as programmable for extra charge. The advantage of using Defendec nodes is wider opportunities in programming. Additionally, Defendec nodes permit to read high frequency measurements, more than 2000 samples per second. NI nodes allow reading one input per second. This excludes using NI nodes by measuring fast changing information as acoustic, vibrations and rotational speed. Nevertheless, it is sufficient for monitoring temperature, voltage and current. In an advanced intelligent WSN systems and in high frequency measurements the Defendec nodes are more suitable due to their flexibility; on the other hand, the usage of NI nodes is often more efficient in research. In adopted WSNs, both hardware components performed their tasks. NI components were measuring slow changing temperature and programming of nodes was not necessary. Defendec node was reading more than 10 impulses per second. In addition, program for rotation speed calculation and data transmission was used directly in the node. As PMS contains many measuring points, which need different sampling rate, it is preferable to use only Defendec components to create a homogeneous system.

Latest versions of MySQL and PostgreSQL database systems can be used as abstraction layer in PMS. Both database systems can be accessed via standard structured query language (SQL) statements, as it handles easily a large number of concurrent connections and solves data storage, replication, and backup challenges.

4.3. Machine tool (production line) components life-span forecast model

In order to provide safe manufacturing process and avoid working tool damages, there is a need to perform replacement or maintenance of the machine tools (production line) components timely. However, unique approach for estimating aging seems here not available, since the wearing (aging) of the components depends on quite different factors like particular equipment, working time, regimes, temperature, loads, materials used, etc. The PMS allows gathering, storing and analysing information needed for estimating the wear of the components. Supported by data, collected by PMS, the forecast models with different complexity levels can be developed. First, it is needed to select most critical components of the machine tool (production line). Next, the key factors, affecting wear of the selected components, should be determined. Third step is collecting of necessary input and output data for the forecast model (the values of the determined key factors and wear parameters). Finally, the functional dependence between the input and output data (the forecast model) should be proposed.

In the following the above described cutting tool utilization is considered as an example. The simplest cutting tool wear forecast model is based on data obtained from the PMS and can be given in the form

$$T_R = T_0 - \sum_{I=1}^{k} T_{MI} \frac{T_0}{T_{VI}}, \tag{2}$$

where

$$T_{VI} = a * V_{CI} + b, \tag{3}$$

T_0 and T_R are the initial and remaining life expectancy time for a tool corresponding to cutting speed $V_{C0} = 320\,\text{m/min}$, respectively. T_{MI} and V_{CI} are the length of the time interval I and cutting speed computed for this time interval using Eq. (1), k is the number of time intervals. The coefficients a and b in Eq. (3) can be determined from life expectancy data for a given tool: 15 min, if the cutting speed is 320 m/min, decreasing the speed about 40% increases the tool life expectancy to 90 min. Assuming linear relationship for life expectancy estimation, one obtains for the coefficients the following values: $a = -0.586$, $b = 202.5$.

Note, that the data, obtained from PMS, is not directly used for composing the model (2)–(3). Actually, the PMS data are considered in cutting tool wearing forecast model (2)–(3) through the cutting speed V_{CI}, which is computed by Eq. (1) and depends on the spindle rotating speed and work piece diameter – the key parameters for describing wear of the cutting tool, obtained from PMS described above. Also, the time intervals T_{MI} in Eq. (2) are not necessarily equal and depend on the spindle rotation speed (if spindle rotation speed changed more than 10 rpm then a new time interval is defined).

Obviously, the proposed analytical model can be considered as a simplified approach, which does not cover all complexities. The model (2)–(3) considers two key factors. There are lots of more complex approaches available for cutting tool wear forecast model development. One such approach is being developed also by the authors of the current study – a multilayer perceptron based feedforward artificial neural network model. As a rule, such models need much more powerful dataset than currently available. The new factors, which can be included in the improved model, are the material of the tool and work piece, vibration of the spindle, temperature, etc.

5. CONCLUSIONS

The real time PMS systems, designed for TUT and JELD-WEN Eesti AS, enables to continuously acquire data from the shop floor with regard to efficiency, malfunctions and productivity. This leads to improved production capacity and cost-efficiency and helps to achieve desired production goals.

The developed prognosis module can be used in the short term and long term planning. It is tightly connected with the maintenance planning to prevent the critical components breaks and to help to increase the productivity and flexibility of the company.

Sample NI and Defendec wireless component based WSNs were adopted for their comparison. Both, NI and Defendec nodes can be used in WSN, but on different measurement frequency levels. Adopting them in PMS, Defendec components are preferable with their higher sampling rate.

Each production SME has differences in manufacturing processes, equipment, priorities and capital resources. That is why the following questions still need to be answered.

– Which data should be collected first?
– Which data have to be saved in the PMS database and for how long (filtering)?
– What is the easiest way to connect different data formats and communication interfaces?
– How to visualize the production data to make it clear to all personnel?

This leads to the general challenging question: is it possible to design a "plug and play" PMS solution that is suitable for most of the production SMEs? Answer for the latter question is open.

ACKNOWLEDGEMENTS

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Reaalajas toimiv tootmise seiresüsteem

Aleksei Snatkin, Kristo Karjust, Jüri Majak, Tanel Aruväli ja Tanel Eiskop

Uuringu eesmärk oli analüüsida reaalaja tootmise seiresüsteeme ja välja töötada paremaid lahendusi. Seiresüsteemi ülesanne on koguda, analüüsida ja jagada reaalajas andmeid sündmuste kohta, mis toimuvad tsehhis. Need andmed peavad aitama tekkinud olukorrale õigeaegselt reageerida. Seiresüsteemide raske juurutamine tootmisprotsessides sunnib uusi lahendusi otsima. Suhteliselt lihtsamad lahendused võivad sobida kõrgema potentsiaaliga reaalaja protsesside juhtimiseks. Käesolevas töös pakutud mudel võimaldab prognoosida võimalike probleemide teket tööpinkides.

PAPER III

Snatkin, A., Eiskop, T., Kõrgesaar, K. (2014). Production monitoring system development. In: *Proceedings of the 9th International Conference of DAAAM Baltic Industrial Engineering*, Tallinn, Estonia, 198-203.

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"INDUSTRIAL ENGINEERING"
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PRODUCTION MONITORING SYSTEM CONCEPT DEVELOPMENT

Snatkin, A.; Eiskop, T. & Kõrgesaar, K.

Abstract: *The main goal of this paper is to offer the concept of the production monitoring system that will help to provide an accurate overview of the shop floor activities, improve asset management, machinery utilisation and production process stability. It will provide diverse information appearance by support of data collection, analysis and storage modules.*
Key words: production monitoring system, remote monitoring, manufacturing execution system, shop floor visibility.

1. INTRODUCTION

The main aim is to offer a design concept of easy-to-use, configurable and cost effective production monitoring system (PMS) for small and medium sized enterprises (SMEs).
One of the problems facing a wide range of manufacturers is how to effectively monitor production lines and machinery to avoid malfunction and unplanned downtime and improve machine and manpower utilization [1]. Resource planning systems should calculate utilization on planning stage and PMS is an instrument that supports keeping this plan in place by supervising the resource state on production stage, together with advanced prognostics tools [2].
Production line and machinery monitoring is the necessary component of the information systems that are used in the production industry to improve efficiency and reduce losses [1].
Despite the fact that a huge number of different production monitoring solutions are offered on the market, there is always place for improvements and simplifications.
Large enterprises are used to a huge number of data to be processed. They have full time staff with expertise to manage specific applications related to production monitoring, data analysis and optimization. At the same time, SMEs also have to deal with the growing number of data to be processed, but normally they cannot afford fully dedicated data experts. Solution to that can be to outsource some of these tasks to a third part or apply simple, affordable and easily configurable monitoring system.
It is clear that successful implementation requires a firm knowledge of the operating principles of PMS. That is why each module of proposed concept will be described first in order to explain how the system should work.

2. PRODUCTION MONITORING SYSTEM

The main task of PMS is to analyse and distribute data collected from the workshop and production line. The data should help the management and operators to get an overview of the machinery and production state.
Additionally to production plan management, there is growing interest in SMEs for asset health and utilisation monitoring, as operating costs of the machinery are considerable part of the total costs. Here special attention is paid to minimize the maintenance cost and time.
Machine state and production monitoring is one of the Manufacturing Execution

System (MES) functions [3]. The main idea of the MES is to integrate separate functions and provide linkage between business and plant floor control systems (see Fig.1).

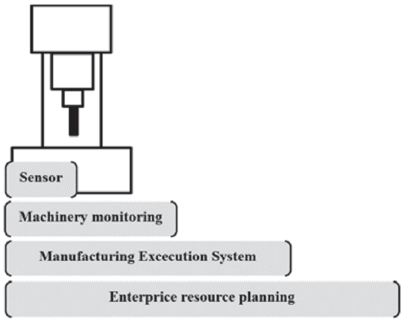

Fig. 1. Position of a MES and machinery monitoring in plant automation.

But if we look through the MES solutions of the leading providers of industrial automation systems and software (like Emerson, Honeywell, Rockwell, Invensys, Schneider Electric, Siemens, etc.), we can see that the core functions of MES are: material and inventory management, scheduling and collection of production data with limited information about equipment state. Support functions are: performance analysis and maintenance management. Most of the solutions are focused on midsize and large companies in chemical, oil and gas, food and beverage, and automotive industries. The process industries have all traditionally been heavy users of MES software, where it ensured that different variables don't exceed set parameters. But the complexity of production processes and machinery are increasing in all industries and more companies may require improved factory shop floor visibility.

3. CONCEPT

Proposed production monitoring system should be comprised of at least five main functions [4,5]: data collection, visualisation, analysis, prognostics and storage (see Fig. 2). Functionality and complexity of each component depends on customers' system specific requirements. Only the base functions and relations are described and additional modules may be added or even removed if required. The concept described below gives the idea of the system functionality.

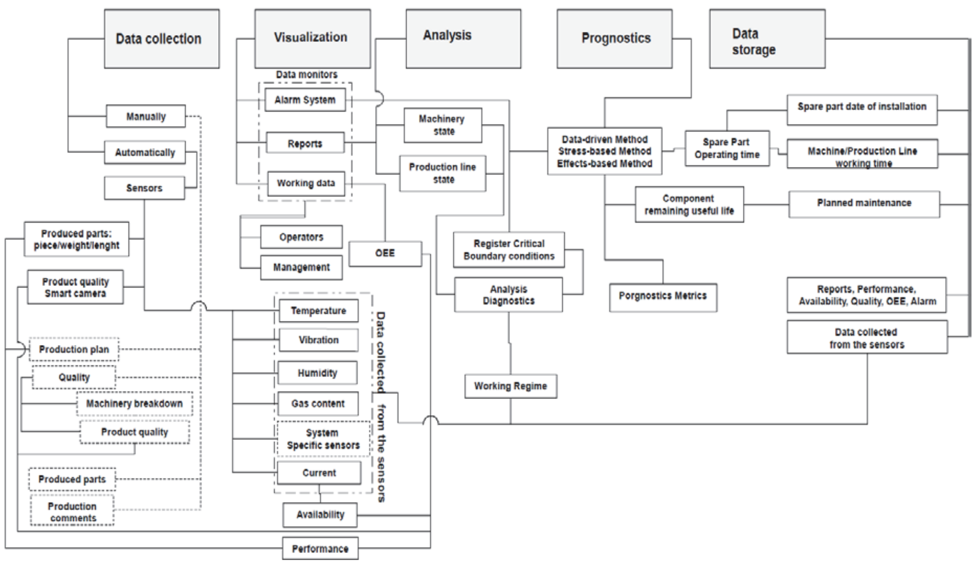

Fig. 2. Concept of a production monitoring system.

3.1 Data collection

Reduced personnel on the shop floors make it necessary to install automated data collection systems.

The most critical part is to identify what to measure, as collected data should help to acquire knowledge. Questionnaires and analysis methods may be used to specify what information is needed. Data not used for decision making could be discarded.

Different factors and criteria should be taken into account when choosing a measurement method and sensor type, like: cost; working range; ease of installation robustness; uncertainty; signal type, sample rate and availability.

Preference should be given to wireless sensors. With the use of energy harvesting it will even more enable sensor remote placement and lower installation costs [6].

The second approach is to maximally apply direct measurements methods, like machine vision systems instead of indirect methods, where collected signal is compared to the optimized signal. But when direct method is used, signal is measured and analysed directly using suitable algorithms. As an example, a smart camera used in machine vision is able to measure tool wear directly. Therefore, direct methods are more preferred than indirect methods [7].

Monitored parameter may be wrongly interpreted if there is no wide feature separation between failure and normal mode.

3.2Visualisation

Data can be presented trough LCD displays, andon boards, mobile device apps or web-based interfaces.

First data should be presented to operators, who will use this information in routine way to get indication of their job and machine state. Data could be customized to be shown in the simplest way (e.g. quantitative measurements replaced by qualitative and KPIs). Contrary, supervisors and service personnel should see more precise reports (historical data of operations performed, measured parameters etc.) for evaluation and finding the areas that may need improvements.

Each company should choose its own key performance indicators (KPIs) and the calculation methods. Most commonly KPIs are related to production output, quality and availability.

Additionally to availability (idle; production; stoppage) rate system must record the reasons of downtime. Operators can input it using touch sensitive screens, keyboard, voice recognition, etc. Multilevel tree structure may be formed to provide more detailed reason description. The figure below represents a three level downtime reason menu for a milling machine (see Fig. 3).

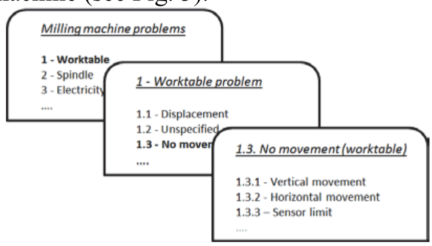

Fig. 3. Multilevel stoppage description.

After each stoppage operator selects the reason from the list, which may be updated by adding new reasons or removing obsolete ones based on the usage statistics. For undescribed reasons the choice “unspecified” can be in the list. When number of such “unspecified” downtime reasons increase to the number of interest, the list of reasons may be revised.

To make downtime cause analysis a PMS should have statistical module to track the downtime changes over the time. Additional module may be developed to measure the maintenance time effectiveness that is related to average time needed to eliminate the reason of stoppage - mean time to repair (MTTR).

3.3. Data analysis

Use of statistics is the most common approach for data analysis to extract useful information from the datasets. Different data mining techniques in analysis are used with its own application area (Table 1.).

Method	Possible application area
Decision tree	Data pre-processing and classification.
Neural network	Pattern detection and predictive models.
Genetic algorithm	Data optimization.
Rule induction	Define relations between different data streams.

Table 1. Example of data mining methods.

Diagnostics, data analysis and prognostics help with the questions that arise during the operation:

- May system continue to operate or should be shut down for maintenance?
- How change of regime will affect the lifetime of the system and KPIs?
- What are the performance, efficiency and quality rate in real time?

3.4. Prognostics

Only if the remaining useful lifetime (RUL) and real state of equipment is known, preventive maintenance may be replaced by condition based maintenance. By use of prognostic methods preparation to maintenance can be done in advance when the system is still running and the failure is known early enough [[8]]. Resources could be focused on parameters of high value systems to determine the most likely scenarios with maximally eliminated inaccuracy and uncertainty.
Knowledge about the physical process determines the regression type to apply (linear, polynomial, exponential, etc.). Prognostic methods are normally divided into the three main groups: Data-driven Method, Stress-based method and Effects based method. These methods can be summarized as follows (see Fig. 4.):

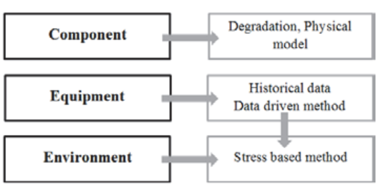

Fig. 4. Prognostic methods description.

3.4 Data storage:

Collected data should be transmitted to a database server. Different database technologies may be used like SQL (e.g. MySQL, Postgres, Oracle Database) or even NoSQL databases (e.g. MongoDB, Cassandra, HBase, Neo4j.). SQL based database systems are more widely used at the moment, as they can be easily accessed via standard Structured Query Language (SQL) statements and effectively solve data storage and replication challenges.
The amount of data saved in the database should be sufficient for data mining. Deciding what to store in the database could improve or reduce performance and thereby influence the time of analysis. It is not reasonable to store every single measurement or even analysed data set in the database when the data is not relevant in the decision making process. If we take measurements with high sample rate it may be better to transfer already selected data (e.g. in WSN node) to database [[4]].
At the same time, cloud based database platforms could be used for more effective resource allocation.
The main challenge here is connectivity and fusion of data form different systems [[9,10,11]] like ERP - enterprise resource planning CMMS - Computerized maintenance management system, etc. One of the solutions can be data integration using XML (Extensible Mark-up Language) platform [[12]].

5. CASE STUDY

The proposed monitoring system was applied and tested on the milling machine DYNA MECH. EM3116 in Tallinn University of Technology (TUT) laboratory. Data acquisition was performed using National Instruments (NI) equipment: Gateway WSN 9791 with NI WSN 3212 thermocouple input node for temperature measure and NI WSN 3202 Analogue input node for Voltage measure. Nodes were secured by magnet brackets to simplify installation. Data visualization was performed through LCD monitor secured to the housing of the machine (see Fig. 5.).

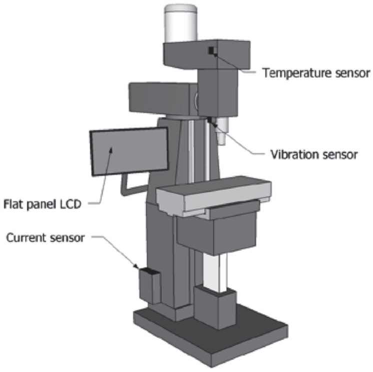

Fig. 5. Milling machine monitoring system.

The choice of NI instead of other solutions was made due to flexibility and optimality of the hardware and software in the concrete case study and using NI LabVIEW software with a graphical programming tool, helped to reduce time for programming.

High sample rate of acceleration measurements didn’t allow using analogue NI WSN due to ZigBee (802.15.4) wireless standard and hardware limitations: WSN 3202 sample rate 1sample/second and ZigBee RF data rate 250kbit/s.

As an alternative for the future research open source hardware platforms like Arduino or Raspberry Pi may be used due to more acceptable price level for SMEs.

Data was saved remotely to PostgreSQL database and to local host as a separate file (see Fig. 6.).

Date: 09.01.2014 Test start time: 14:45:00

Timestap (1s)	Temperature Celsius	Timestap (1s)	Current Ampere
303	20,864441	303	0,405514
304	20,864441	304	0,359547
305	20,866158	305	0,342834
306	20,866158	306	0,223744
307	20,866158	307	3,182226
308	20,866158	308	3,192675
309	20,866158	309	2,994192

Fig. 6. Example of collected data set.

During the test were determined the set points for idle, production and heavy load operation for different cutting regimes of S235JRG2 steel (Fig. 7.).

Cutting depth	RPM	Workable movement	Current Ampere
0.5	300	150	3.0
1	300	150	3.2
1.5	300	150	3.4
2	300	150	3.7
0.5	450	300	3.2
1	450	300	3.5
1.5	450	300	4
1.75	450	300	4.3

Fig. 7 Current for different regimes.

Obtaining sample data of the failure progressions to define alarm set points for measured parameters posed to be a real challenge, as systems are normally not allowed to run until failure and the vital parts are always tried to be replaced before they fail. Therefore, as an alternative, statistical process control (SPC) was proposed for continuous automatic calculation and update of warning limits (upper/lover limit control).

After the survey (interview of operator) were determined the most common breakdown and quality problems for such type of milling machine that helped to make the list of problems for visual model.

Main window of visual module was developed using PHP language, jQuery, jqPlot allowing seamless object-oriented data updating without refreshing the whole page (see Fig. 8.).

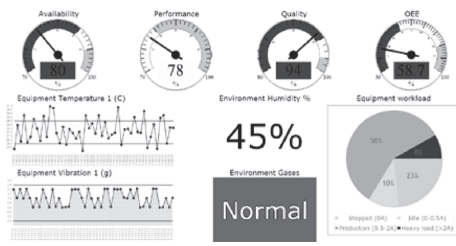

Fig. 8. Developed visual module for PMS.

6. FURTHER RESEARCH

Standardized metrics of production monitoring system will help to compare different solutions on the market and evaluate effectiveness of the existing ones. Methodology should be described how to determine what critical data to monitor and visualise. Also solutions for integration and data fusion with higher level systems (e.g.

ERP) should be developed. Proposed concept should be optimised for production lines and group of machines, where you can compare the status of all equipment to provide the total production area overview.

9. CONCLUSION

PMS concept was offered and applied for the milling machine. It provides transparency on the shop floor and improves manufacturing competitiveness. System offers predictive functionality and helps to prevent the critical components breaks.

12. ACKNOWLEDGEMENT

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PAPER IV

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PRODUCTION
MANAGEMENT

Production monitoring system development and modification

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Abstract. Main attention of this paper is paid to the development of a simple, but efficient concept of a real time production monitoring system. The goal is to offer an effective concept, which will help to provide an accurate overview of the shop floor activities by diverse information appearance and improve asset management, machinery utilization, and production process stability. The subtask considered includes description of the design of a visual module for the proposed production monitoring system for a certain type of micro, small and medium sized enterprises.

Key words: production monitoring, remote monitoring, manufacturing execution system, shop floor visibility.

1. INTRODUCTION

Industrial systems are becoming more complex due to integration of new technologies. At the same time, it makes maintenance and monitoring activities more expensive and complicated to get the reliable data on time. This situation motivates the researchers to look for innovative ways of production monitoring and maintenance. Equipment performance and condition monitoring was always an essential part of the information systems used in industry to improve effectiveness and to minimize unplanned downtime [1]. The sector of SMEs takes considerable part of most economies. In business areas, where capital and entry costs are high, SMEs' share is small. But from the other point, SMEs can dominate in niche markets where larger companies are not so active due to low sales volume. This narrow focus can give good results while developing totally new products and solutions. The question arises: how to increase SMEs' productivity and efficiency with the lack of resources. And one of the solutions can be an affordable, easy to integrate production monitoring system (PMS) based on open source software and hardware. As many SMEs may not have the possibilities of expensive production monitoring tools, this alternative solution can help to increase productivity. SMEs often lack the financial resources to hire experienced specialists or acquire expensive machinery with integrated monitoring tools. In many cases, production equipment used, even for the same functions, is from different producers. All this complicates the integration of embedded monitoring solutions to one system and analysis of collected data. Trade-off should be found between an expensive system with extensive functionality and cost effective solution. The proposed PMS could help to overcome these challenges. And it should be considered not as a tool to control the operator behaviour, but as a tool to reduce burden on operators and simplify reporting.

In the first part of this paper, production monitoring system concept for SMEs is described that will provide the basic idea of the system structure. And the second part of the paper is focused on the case study of a visual module development.

2. PRODUCTION MONITORING SYSTEM

Production monitoring data can be classified into two major groups: status of resources and status of jobs [2]. Status of jobs is related to data of each completed operation, estimated production time, sequences, etc. It provides information about the order flow for improvement of production sequences. Real time overview of

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the production process supports paperless reporting approach. Thus, comparison of planned and actual production numbers is possible at any time and allows more realistic scheduling that will help to meet delivery deadlines.

The second group, the so-called status of resources, is closely connected to machinery, personnel and working environment monitoring (Fig. 1). Here the machine event monitoring shows machine workload, downtime, availability, and performance. If the machine is not working, operators know exactly why and can rearrange the planned operations on time, which saves time and cost. Such data give detailed real-time and historical information of what is/was happening on the shop floor with the machinery. Personnel monitoring covers optimal movements tracking; planned versus actual manpower data, etc. Different indoor positioning systems may be used for people and equipment location tracking [3] that is part of the global production effectiveness (GPE) concept [4]. Working environment is seen here as a part of the "status of resources" group, as it affects the personnel comfort and safety. That directly impacts production efficiency. Here the requirements for ventilation, intensity of light, noise level, CO_2 concentration, vibration, magnetic field, etc., are regulated and checked by the international labor organizations (e.g., C148 – Working Environment convention from 1977) and by local labour institutions.

Data about the status of jobs and resources groups support functions of material and resource planning systems and provide feedback from the workshop. Keeping all departments informed of what is going on in the workshop, helps to timely react on unplanned situations. Production monitoring system does not directly control machinery, but tracks it.

In many cases, data subsets from different groups, described above, should be reviewed as a single data set to identify, e.g., reasons of quality problems, unplanned downtime, low performance, etc. Detailed status on every machine in the PMS is supported by such key

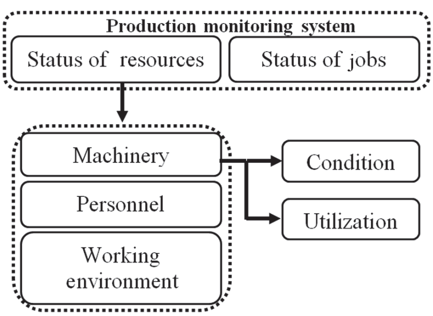

Fig. 1. Production monitoring system classification.

performance indicators (KPIs) as availability, performance, quality rate, and overall equipment effectiveness (OEE). For machinery fault diagnosis different strategies can be used:

- Preventive maintenance – periodically shut down services for manual inspection. One of the drawbacks of such strategy is that equipment should be normally out of operation during the inspection to detect problems.
- Condition-based monitoring – fault diagnosis by means of appropriate observations based on acoustic signal, temperature, electrical current, vibration monitoring, etc. Condition-based monitoring is a more preferable strategy due to automatic diagnostic and predictive nature.

PMS systems can be seen as a subset of the Manufacturing Execution System (MES) that comprises the same functions as data collection and acquisition, maintenance management, resource status, product tracking, and production performance analysis [5,6]. However, machinery monitoring, which is one of the main functions of the PMS, is not the primary goal of the majority of MES solutions. The reason is that the initial idea of MES was to provide higher level systems, e.g., enterprise resource planning (ERP), with the required production status data from the workshop. To support the accurate production plan scheduling through material movement tracking and inventory management. There are several standards and regulations (e.g., ISA-S95) that ensure MES robustness and interconnection with other systems. Through that it may have influence on the PMS development.

At the same time, PMS is closely related to supervisory control and data acquisition (SCADA) systems that conventionally were mostly responsible for process monitoring and control operations, but nowadays come with more advanced functions like reporting and scripting capabilities, performance calculation, and integration with MES/ERP.

Numerous specific software products exist to manage production processes. They may be presented as MES, but functionality is varying depending on customer expectations or tools used (e.g., spreadsheets, comprehensive management applications). The basic functions of MES solutions, developed by the leading providers of industrial software and automation systems, are inventory management and collection of production state data with limited equipment state data with support functions like performance analysis and maintenance management (Table 1). The main focus of these solutions is on midsize and large companies, mostly in process (chemical, oil and gas, food and beverage) and automotive industries.

The main disadvantage of these solutions is investment costs (software purchase, customization, testing, implementation, maintenance, etc.). In some cases such

Table 1. Example of some of the advanced MES solutions provided

Vendor name	Product name	Core functions
ABB	cpmPlus Suite	Quality management, material and warehouse management, visualization, process optimization and decision support, electronic work instructions, production performance reports
Apriso	FlexNet	Warehouse, quality maintenance, labour activities, managing and executing production
Aspen technologies	aspenOne	Performance analysis, production resource management, production dispatching and execution
Emerson process management	Syncade	Production operations, inventory management, quality management, maintenance and machinery health management
Forcam	Factory Framework	Order data management, personnel data, production data management, machine data collection, process data management and traceability
iTAC software	iTAC.MES.Suite	Material logistics, quality management, production planning and management, production and machine data collection
IBS	IBS:MES	Operational data, machine data, tool administration, resource and service management
GE intelligent platforms	Proficy for Manufacturing	Order completion status, interactive schedule planning, material delivery management, maintenance management
Honeywell process solutions	Intuition Executive	Planning and scheduling, supply chain and operations management, equipment monitoring, performance monitoring
Invensys	Wonderware MES	Electronic work orders, operations management, performance management, quality management, product traceability, inventory
MPDV mikrolab	Hydra	Material and production logistics, machine and process data collection, tool management, quality assurance, personnel scheduling
Rockwell automation	FactoryTalk	Production management, asset management, quality assurance, performance management, control system connectivity, automation control programming
SAP	SAP ME SAP MII	Production management, product traceability, maintenance activities, labour tracking, production metrics, material tracking
Schneider electric	AMPLA	Asset utilization and performance metrics, material tracking, quality management, labour tracking, energy consumption tracking
Siemens	SIMATIC IT	Quality control management, product tracking, mapping of manufacturing processes, collaboration with R&D, process efficiency and utilization management

systems may have weak re-configurability or require expert knowledge of the system that may affect flexibility of the company, when every change in configuration (machines, materials, design, suppliers, etc.) must be prepared by the software supplier and imported to the system [7]. There is a lot of companies providing solutions with limited functionality and operating in a specific area (e.g., Evocon Line Efficiency, Wintriss ShopFloorConnect). Such solutions are normally designed to get the most basic inputs form the production line (machine): unit and flow speed counting, job list, downtime and quality reports, etc. Apart from that, many production companies are developing and implementing their own unique niche production monitoring solutions to suit their specific needs rather than to buy or rent one. Complete history of the work shop activities supports the ability to review quality problems on any life stage of the product that is one of the product lifecycle management (PLM) functions [8].

3. CONCEPT

Integral parts of PMS are data collection and analysis, prognostics, visualization, and storage (Fig. 2). Complexity of each component may differ according to customer requirements [9–11]. It means that the system is expandable: additional custom modules may be added to form one integrated platform.

PMS does not provide main functions of the production scheduling system and should work closely with

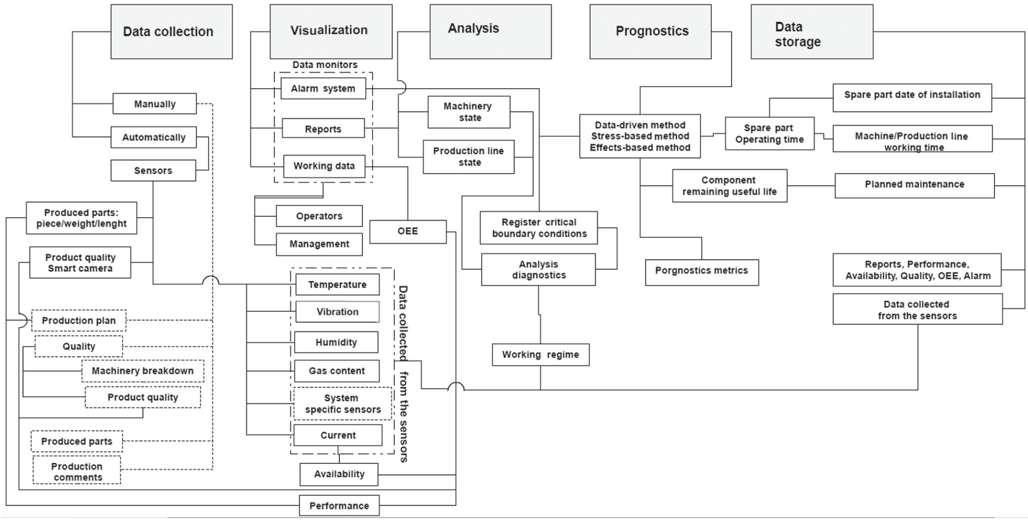

Fig. 2. Simplified concept of a production monitoring system [11].

production planning systems to exchange data (e.g., through MES, ERP, etc.). As an example, such data as the number of pieces to be produced and ideal cycle time to calculate machine performance should be inserted once and used in different systems. Standalone solution may require a number of manual inputs and have limited functionality.

The more sensors will be integrated in the system, the more data will be generated that should be handled. But processing this growing number of data through traditional database technologies will be challenging. This problem is directly related to the concept of Big Data. But the use of Cloud computing may help to simplify these data processing issues [12].

Preferably, a web based user interface, based on open source software, should be used to cut the costs. At the same time, custom open-source software may lead to the lack of qualified support and require more effort to integrate with existing equipment [13]. To mitigate these risks, integration may be supported by third parties (university research teams, private companies) and special dedicated online communities. Different motivation points for people to participate in such online communities are considered [14] (e.g., benefits from the work of someone else, making a research project, etc.). Despite some drawbacks, such software and hardware supports principles of open research and collaborative knowledge creation. The design of a PMS and its parts requires interdisciplinary research: to incorporate data mining, software, hardware, user interfaces, ergonomics, etc. As software architecture and engineering is not in the scope of this research paper, only basic software functions will be described.

3.1. Data analysis and prognostics

Different data analysis techniques are used to retrieve useful information from the collected data. And by the support of prognostics the most likely scenarios are determined with maximally eliminated inaccuracy and uncertainty. Here focus should be mostly on high value parameters. Along with that are additionally required developments in advanced sensor technologies and incipient fault detection techniques.

It is a real challenge to obtain samples of the failure progressions, as most of the critical systems are not allowed to run until failure and vital parts are replaced. So in this case limited analysis may be performed. Failure degradation of some systems takes a long time that complicates the research. Solution to that is to run experiments in a laboratory environment, to accelerate the aging. But studies conducted in research laboratories often neglect certain practical considerations from the real-life situations.

3.1.1. Data analysis

Together with different data mining techniques (e.g., neural networks, genetic algorithms, decision trees) to identify a possible problem, statistical process control (SPC) may be used to calculate upper and lower limits. That will help to inform operators about possible abnormal conditions. Such methods may be applied to construct control charts by use of data measurements on a continuous scale, e.g.:

- Shewhart control charts.
- Exponentially-weighted moving average chart (EWMA).
- Cumulative sum control chart (CuSum).

To construct an X-bar chart (control chart) or R-charts (range chart), the following steps should be done:

- Measure (subset) data points.
- Calculate mean and range.
- Calculate standard deviation.
- Calculate upper and lower limits (subset size determines the constant to be used in equation).
- Construct plots.

In a visualization module, where control charts are presented, collected data (e.g., temperature, current, vibration) are plotted in a time order. On these control charts, the central line for the average is shown together with upper and lower control limits. By comparing the real time data with the historical one, operator can draw conclusions whether the process is stable. Out of control signals should be marked. Chart axis scale should be automatically updated.

As an example, a subset of five readings are calculated using the following equations [14]:

$$\begin{aligned}
&Central_line_\bar{\bar{X}} = \frac{(\bar{X}_1 + \bar{X}_2 + \ldots \bar{X}_k)}{k},\\
&Central_line_\bar{R} = \frac{(R_1 + R_2 + \ldots R_k)}{k},\\
&\bar{\bar{X}}_UCL = \bar{\bar{X}} + A_2\bar{R}, \quad \bar{R}_UCL = D_4\bar{R},\\
&\bar{\bar{X}}_LCL = \bar{\bar{X}} - A_2\bar{R}. \quad \bar{R}_LCL = D_3\bar{R}.
\end{aligned} \tag{1}$$

Here k is the number samples (subgroups). If subgroup size $n = 5$, values of the formula constants are: $A_2 = 0.577$, $D_3 = 0$, $D_4 = 2.114$.

Additionally, the area between limit controls and grand average can be divided into more regions:

$$\begin{aligned}
&1/3_UCL = \bar{\bar{X}} + (\bar{\bar{X}}_UCL - \bar{\bar{X}})*1/3,\\
&2/3_UCL = \bar{\bar{X}} + (\bar{\bar{X}}_UCL - \bar{\bar{X}})*2/3,\\
&1/3_LCL = \bar{\bar{X}}_LCL + (\bar{\bar{X}} - \bar{\bar{X}}_LCL)*2/3,\\
&2/3_LCL = \bar{\bar{X}}_LCL + (\bar{\bar{X}} - \bar{\bar{X}}_LCL)*1/3.
\end{aligned} \tag{2}$$

3.1.2. Prognostics

As prognostics is becoming more widely applied in different disciplines, all the definitions describing it are subject for further development and refinement. But most of the definitions agree on the prediction aspect. A prognostic is usually used to predict one of several related measures [15, 16]:

- Remaining useful life (RUL): the amount of time the component will continue to meet its design specification.
- Time to failure (TTF): the time a component is expected to fail.
- Probability of failure (POF): the failure probability distribution of the component.

According to various requirements, there are different approaches, from a simple (e.g. degradation trends) to relatively complex ones (e.g. physics-based model methods). The regression type (e.g. polynomial, linear, exponential) to be applied is determined by the knowledge of the physical process. And prognostics methods may be separated into three different groups: data-driven method, effects-based method, and stress-based method.

In *the data-driven method* the prognostic model is based on data, collected from the system. In general, it is an easy and fast method to implement. This method considers historical data to estimate the lifespan under normal usage conditions. One of the most popular parametric models for that is the Weibull distribution [16]. And the most general expression of the Weibull probability density function is given by the three-parameter Weibull distribution:

$$f(t) = \frac{\beta}{\eta}\left(\frac{t-\gamma}{\eta}\right)^{\beta-1} e^{-\left(\frac{t-\gamma}{\eta}\right)^{\beta}}, \tag{3}$$

where t is time; γ is the location parameter ($\gamma = 0$, yields the two-parameter Weibull distribution); $f(t) \geq 0, t \geq 0$ or $\gamma, \beta > 0, \eta > 0, -\infty < \gamma < \infty$; β is the shape parameter. If $\beta > 1$, the failure rate is increasing; $\beta = 1$, the failure rate is constant; $\beta < 1$, the failure rate is decreasing; η is the scale parameter.

Main disadvantage of such method is that operating conditions are not considered. Components operating under different conditions than modelled are going to fail earlier or later. And this method requires sufficient number of samples that were run until failure, but it is not always feasible.

The effects-based method considers degradation of a component. Degradation effect should be slow enough for the decision to be made. Degradation can be a function of several measured variables. Model development requires a thorough understanding of the system, in other words, clear understanding of the degradation mode (e.g., physical model). Typically, physics-based algorithms assume that new equipment is perfectly designed and produced.

The stress-based method, additionally to the data-driven method, also considers an environmental impact (vibration, temperature, humidity, etc.). This method can provide a more precise assessment of the RUL.

The simplest class of the stress-based methods uses an ordinary least squares regression model to predict the failure time. By use of such information as a component load, temperature or other working conditions, in addition to the time to failure data, a multivariate regression can be performed to predict the expected failure time. In this model, the slope is related to the stress, caused by operating conditions. Another approach is to use multiple data-driven models, which account for different working conditions. Or in special cases a single data model with a correction factor, which accounts for a stress based information [17]. It can even be a simple linear regression model that includes prior observations of explanatory variables and response variables as a failure time.

The proportional hazards model (PHM) [16,18] is often used to combine failure data with environment (stress) data. It uses environmental condition information as covariates to modify a baseline hazard rate function:

$$\lambda(t;z) = \lambda_0(t)\exp\left(\sum_{j=1}^{q}\beta_j z_j\right), \tag{4}$$

where $\lambda_0(t)$ is the arbitrary baseline hazard or function; z_j is a multiplicative factor, explanatory variable or covariate; and β_j is a model parameter.

Of course, a prognostic is not feasible in all cases. For example: getting dust into the bearing is an uncertain event and you cannot predict it. But if you measure the state of the bearing (vibration, temperature, etc.), you may be able to detect the upcoming failure and replace (take precautions) before it fails. You can also try to eliminate uncertainty by preventive/protective measures (e.g. dust seals), which you can take based on the root cause analysis from the machine stoppages explanatory data of a PMS system.

3.2. Data collection

Parameters of interest should be decided for each customer/case separately. Starting from analysing an enterprise, main problems may be mapped and relevant KPIs selected that are in line with the objectives defined. Indeed, comparing to larger companies with more complicated structure, the process of selecting, changing, and reviewing of KPIs inside SMEs could be more likely to be performed with relative ease. Different approaches may be used to select proper data to be collected and visualized (customer interview, questionnaire, etc.). As an example, questionnaires may describe such points as the definition of a problem or goal to be solved, minimum requirements to be achieved, equipment to be monitored, known limitations and restrictions, responsible individuals, etc.

As there is always a risk that the system may be rejected by the operators (e.g., because of intrusive data inputs), information should be maximally collected automatically.

In industry (and laboratories), to get a readable data from a sensor, signal conditioning module, analogue to digital converters and data loggers are used. Typically total cost of this equipment is quite big, but cost effective solutions are available, as, for example based on Raspberry Pi single board computers and Arduino single board microcontrollers. Raspberry Pi that can be used as a data logger (local host) does not have an analog-to-digital converter (ADC) and requires external ADC to allow sampling of an analogue signal. But in this case, care must be taken as Raspberry Pi is not running real-time operating system (RTOS). Therefore, Arduino board that has ADC may interface between the sensor and Raspberry Pi. There is also a ready combination of platforms like UDOO, Beaglebone and others available on the market.

Preferably, wireless solutions should be used, like wireless sensor networks (WSN) that help to reach difficult accessible locations, by maximally eliminating wiring for quicker installation. There is a number of ways how this network architecture may be implemented. Large networks can be decomposed into clusters, where cluster could have either single-hop or multi-hop communication [19], as well as a combination of wired and wireless technologies or only wired communication could be used in more data-intensive operations or stringent environments. Different energy sources may be applied using piezoelectric materials (e.g., energy harvesting from vibrations), thermoelectric converters, photovoltaic approach, etc. Also Field Programmable Gate Arrays (FPGAs) may be used to extend the functionality of WSN controllers [20].

3.3. Visualization module

The process of development of the graphical user interface (GUI) is closely related to data, collected in the workshop. One of the ideas of visualization is to present complex data in a simple way. It may help to find patterns in a large amount of data and take quick decisions. Data visualization should be available between company's different departments. Proposed production monitoring system visualization module may be presented as a three-level structure. Table 2 below shows the main tasks of the GUI on different levels. These tasks are not limited, and depend on customer requirements and investment costs.

In manufacturing environment, it is not always ergonomic for operators to use keyboard and mouse, so in some cases touchscreens may be preferred. But when developing GUI for touchscreens, not all "fundamentals" of mouse & keyboard interfaces should be used, e.g., if quick inputs are closer to the corners to reach easily with the mouse pointer. As for big touch

Table 2. Proposed structure of GUI for the production monitoring system

Level	User/Department	Main tasks
View 1	First-level managers and experienced workers (working foreman, operator)	Workplace KPIs, produced items, quality inputs, system condition monitoring
View 2	Mid-level managers (foreman, department leader)	Combined department/ workshop view, extended reports (performance comparison), reporting and statistics module, system administration
View 3	Upper-level managers (management, maintenance manager)	Production statistics, overall workshop performance, forecasts

screens, operators will have to stretch they hands to reach the corner of the screen.

When the operator has to make choices from the data presented (e.g., menus, buttons), the number of choices should be limited to decrease the responding time according to the Hick's Law [21,22]. In some cases it is possible to achieve it by combining or removing some items. Also, frequently accessed items should be of large size and with the possibility to replace its position on the screen to be more suitable for each operator that is in line with Fitts's law [23,24].

Here some of the Shneiderman's design principles [25] may be useful, like (1) an identical terminology used through all the GUI menus, (2) possibility for advanced users to use shortcuts, (3) system designed so that the user cannot make serious errors, (4) the undo possibility. Regarding the reverse functionality, it may encourage operators to try unfamiliar options. But review of main changes should be stored. Despite the number of advantages, the following limitations should be considered:

- It may be faster to type words with conventional keyboard for most of the users, comparing to on-screen keyboard.
- Finger size defines the size of icons, and, e.g., haptic technology should be used as a feedback that the option has been selected.

It is beneficial to take these advices when designing GUI for PMS, but it does not warrant decrease of time for critical responses. As there is no unique approach that will be suitable for all production environments, each interface should be possible to adjust on site. And the need of additional prompting of confirmation requests, when the option is selected, should be definitely discussed with the users.

Preferably, client server model should be replaced by web-based platforms with operating system independence and remote functionality, but here the question about the web-based security arises, as data is more easily to be accessed remotely by 3rd parties and web page loading speed from the web server may be lower comparing to desktop software. Of course, there is a number of hacks existing to improve performance of web page loading (e.g., AJAX, JavaScript/CSS files delayed loading, etc.). But these questions are related more to software engineering and architecture.

3.4. Data storage

A data storage module is responsible for data archiving, distribution, and storage. Collected data could be saved to on-site database server (SQL or NoSQL databases) or to cloud-based platforms. Cloud storage is closely related to cloud computing that is consisting of different services, e.g., (1) platform as a service, (2) infrastructure as a service, (3) software as a service. It may help to cut the investment costs of the designed system, but a drawback is the responsiveness of the system compared to the on-site server.

Data may be stored in different formats like ASCII, XML, Binary, Database Files, etc. Depending on the application, they have their strengths and weaknesses. Such factors as data-streaming speed, human readability, file size, and exchangeability should be taken into consideration. It should also be decided for how long data should be saved in the databases. Possible system expansion in the future should be considered, as it may bring changeover in database structures. Data should be protected (e.g., network security standards). As a preventive tool of user logging management, system privileges may be applied. Policies inside the company should exist to maintain data protection.

If by some reasons there is no connection with the remote database, local data acquisition terminals should keep collected data until the connection is restored and synchronize with the central database. One simple example can be how the Raspberry Pi receives data from the Arduino controller (Python script) and logs it to remote SQL server with the possibility to save it on local SQL server that it runs itself (Fig. 3). Additionally, Arduino could be supplied with a SD card for logging as a fail-safe in case of data connection failure between Arduino and Raspberry Pi.

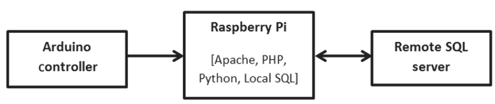

Fig. 3. Example of data logging.

4. A CASE STUDY

Increasing the capacity of a bottleneck production line is usually a long and investment-heavy undertaking and therefore a decision was taken to apply automatic PMS solution on a profile planing line of a mass-production woodworking company with a purpose of collecting data for analysing the need for investing in a new production line. Since the cost of the considered solutions was over the budged, a custom solution was developed for specific needs of the company. And separately a visual module for milling machine DYNA MECH. EM3116 was developed at the Tallinn University of Technology.

The case study focuses on creating custom GUI for application in daily work, instead of time consuming and tedious paper reports.

4.1. GUI development for the production line

The GUI for the PMS was developed by authors as a web-based application. The use of dynamic web pages [26] with the support of AJAX (Asynchronous JavaScript and XML) technology allows updating user interface specific objects and responding to submission events. The idea was also to use tablet devices with Android operation system to lower the cost of the system. Web-based approach allows the use of a wide range of devices with graphical interface support.

To simplify development, open source PHP package – XAMPP version 1.6.6a was installed (that includes MySQL database version 5.0.27; phpMyAdmin MySQL version 2.11.7.1; FileZilla FTP server version 0.9.20b; PHP ver. 5.2.0; and Apache web server version 2.2.3).

Two main GUIs where developed for user interaction with the system for the operator and the quality inspector of the end product.

The GUI for View 1 (Operator screen) – consists of 4 main parts (Fig. 4):

- Screen header – displays the machine id, machine name and the current shift number.
- Stoppage reasons and times – stoppages in chronological order.
- Stoppage overview – stoppage reason summary.
- Shift overview – displaying various machine/production line specific detailed information.

Additionally, there are 3 buttons in the top right corner of the Operator screen for *reporting a breakdown* to the technical department that is a link to an external system; *shift report* which is showing the current shifts more detailed summary and *end shift* button.

Clicking a stoppage in the *"Stoppage reasons and times"* column will open a new screen for specifying a stoppage group and then based on this selection the stoppage reasons in this group will be displayed. There is a possibility for a breakdown registration with a time interval (Fig. 5).

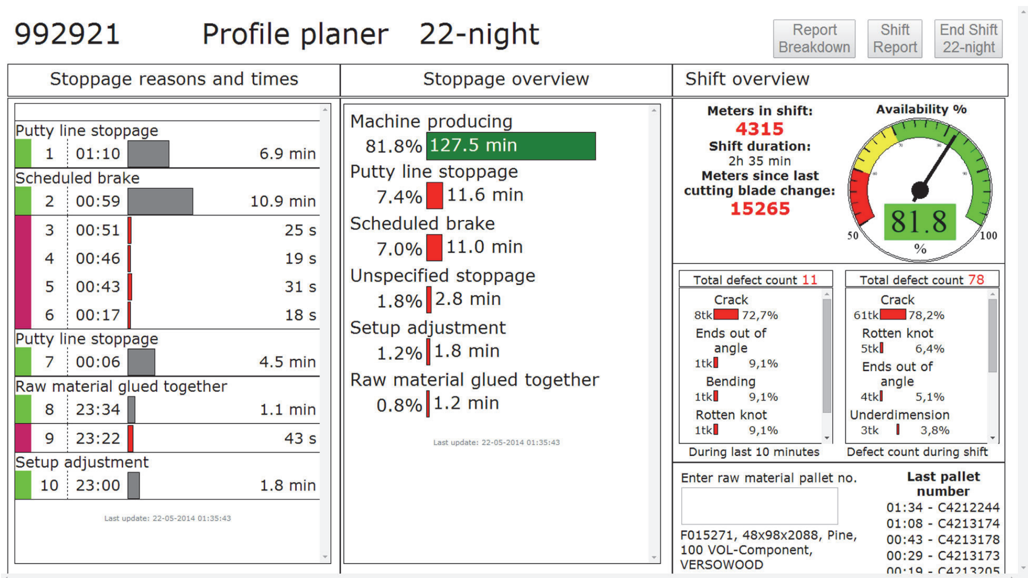

Fig. 4. Machine/Operator screen.

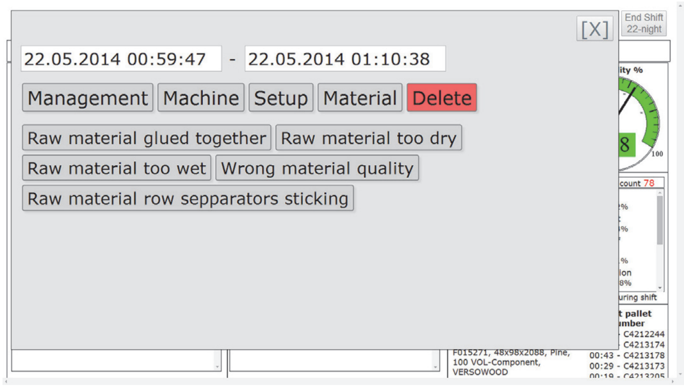

Fig. 5. Machine/Operator screen stoppage reason selection.

Shift overview column in the Operator screen consists of 3 parts: shift overview, quality overview, and raw material consumption registration. In the shift overview section, there are several key performance indicators that are the main measurements of the effective use of the line – meters produced in shift and machine availability. Machine availability is calculated based on the signals from a rotary encoder that measures the length of the material that is molded. Once there is no material under the encoder, the line must be having a stoppage. The sum of stoppages deducted from the total shift length gives the available production time for the machine. In connection with produced meters per shift an important indication for the line can be calculated – the average production speed.

The quality overview shows the data that is entered by the quality inspector, who is inspecting each product that is produced. The information is split in two sections – quality summary for the last 10 minutes and for the whole shift. Reason for such separation is that recent changes in quality of the products may not be visible in the scheme of the whole shift.

Raw material registration is done via a barcode scanner that reads the information from the pallet that is fed into the line. Additionally to the Operator screen, there is a possibility for the workers to look at a report that uses Statistical process control (SPC) approach with the Planner speed (Fig. 6).

The report shows the actual average speed of the line per minute and displays the minimal and maximal speed range based on the product information of the currently produced item.

The Quality screen (Fig. 7) is the main screen for the Quality Inspector of the end-product and is built to give a quick feedback for the quality inspector and the operator. The quality GUI consists of 4 parts:

- The header with machine and current product information and the starting time for the last product (top left of the screen).
- Reporting buttons for each of the predefined defects that should be reported (middle left of the screen).
- There are buttons for viewing the *Last 10 registrations* and *Deleting a registration*; *Current shift report* for displaying a report grouped by products and total for the shift; *Previous shift* report which shows the data of the previous shift; and *Product change* for defining what product the line is producing at the moment.
- Total Defect Count.

The data from the Quality GUI is used for creating a base report for importing to excel for further analysis for the mid-level managers. The Quality GUI allows the workers and mid-level managers to make quick decisions about the raw material they should use for specific product and the weekly Excel report gives a good base for choosing the biggest defect group to work on.

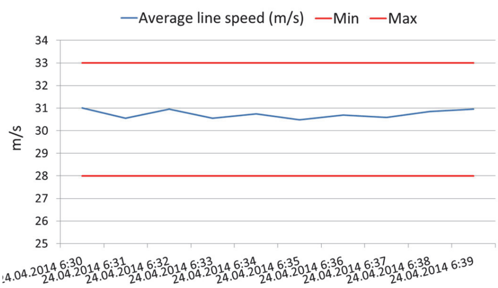

Fig. 6. Average speed during a shift (data grouped by minute).

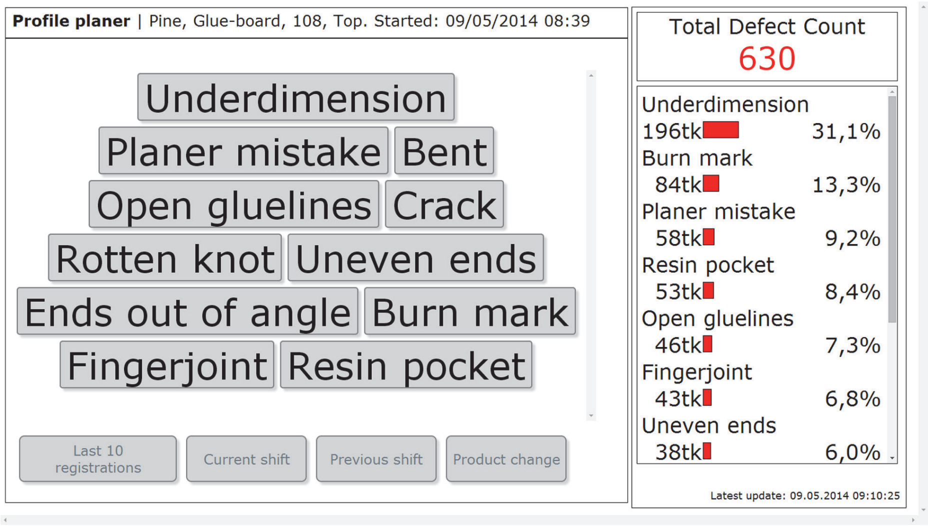

Fig. 7. Quality Screen.

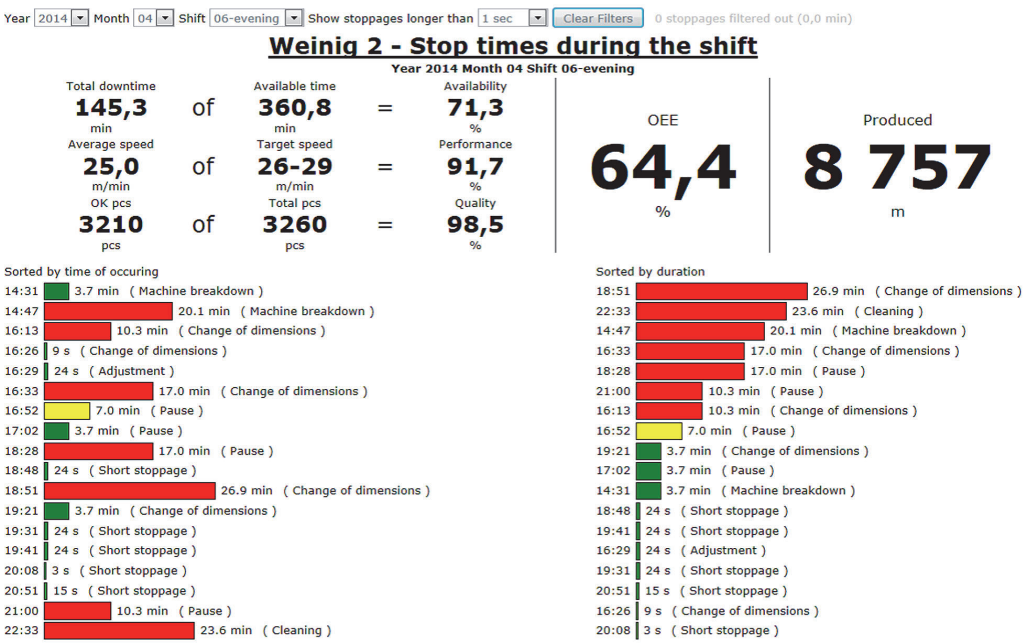

Fig. 8. Reporting module for production line (View 2).

Additionally to the GUIs, a Reporting module for production line was developed and implemented. The Shift report (Fig. 8) provides an overview for the first and middle level management and the operator about the shift results and gives them an idea, what were the biggest stoppage reasons. The user needs to select a year, month and a shift for the report to be displayed. Additionally, the user can filter out stoppages based on duration.

The reports main feature is the OEE breakdown into 3 components and displaying the parameters for the calculation of these components. This gives a very clear indication what component needs to be worked on and gives a clear direction for the root cause analysis. Multiplication of Availability, Performance, and Quality components will result in OEE. As the main indicator of the operators good work is the high quality product that the line produced, the Produced meters are displayed on the report. Additionally the report features the stoppage reasons, sorted chronologically and by their duration. With just a glimpse, the operator can see the longest stoppage and browse through the history of stoppages chronologically. There is a possibility to automatically generate a Pareto chart that will show the summarized version of the stoppages by grouping them together by type, thus enabling to see the biggest stoppage reasons for the whole shift.

Another report that was designed is the summarized report by week, showing the same information as the shift report except for the individual stoppages. Additionally, it displays the products that were produced during the week and the statistics for the individual products. Rows coloured red in product data give the indication where the actual average speed is over theoretical speed, meaning that the ideal cycle time for the product needs to be remeasured and corrected in the system or there are some mistake (Figs 9, 10). This report is ideal for looking at the bigger picture of the production line statistics and making decision for the longer term. That is why it is a good report for the middle and high level managers to get a quick overview.

The system described is in everyday use now and to analyse its effect on the productivity thorough research should be done. According to the data collected from the bottleneck production line during the last two months period compared to the last year average, productivity (units per hour) increased by more than 30%.

4.2. GUI development for the milling machine

Obtaining sample data of the failure progressions to define alarm set points for measured parameters posed is a real challenge, as systems are normally not allowed to run until failure and the vital parts are always tried to be replaced before they fail. Therefore, as an alternative, statistical process control (SPC) was proposed for continuous automatic calculation and update of warning limits (upper/lover limit control). After the survey (interview of operator), the most common breakdown and quality problems were determined for such type of milling machine that helped to make the list of problems for the visual model [11].

Product data

Production start	Production end	Product id	Product Info	Meters	Duration (min)	Running time (min)	Average Speed	Theoretical Max Speed	Performance
12.05.2014 00:00:03	12.05.2014 01:57:43	1979	pine component 93 2077	1 362	118	43	31.4	36.0	87.2%
12.05.2014 01:57:43	12.05.2014 05:58:18	1980	pine glueboard 93 2077	3 838	241	119	32.3	36.0	89.6%
12.05.2014 05:58:18	12.05.2014 07:40:07	1981	pine glueboard 93 2077	3 143	102	91	34.4	36.0	95.5%
12.05.2014 07:40:07	12.05.2014 14:03:46	1985	pine glueboard 93 2077	6 613	384	195	34.0	36.0	94.5%
...									
15.05.2014 14:32:27	15.05.2014 21:31:13	2035	pine glueboard 93 890		3 559	419	142	25.1	24.0

Fig. 9. Summary report group by product data for upper- and mid-level managers.

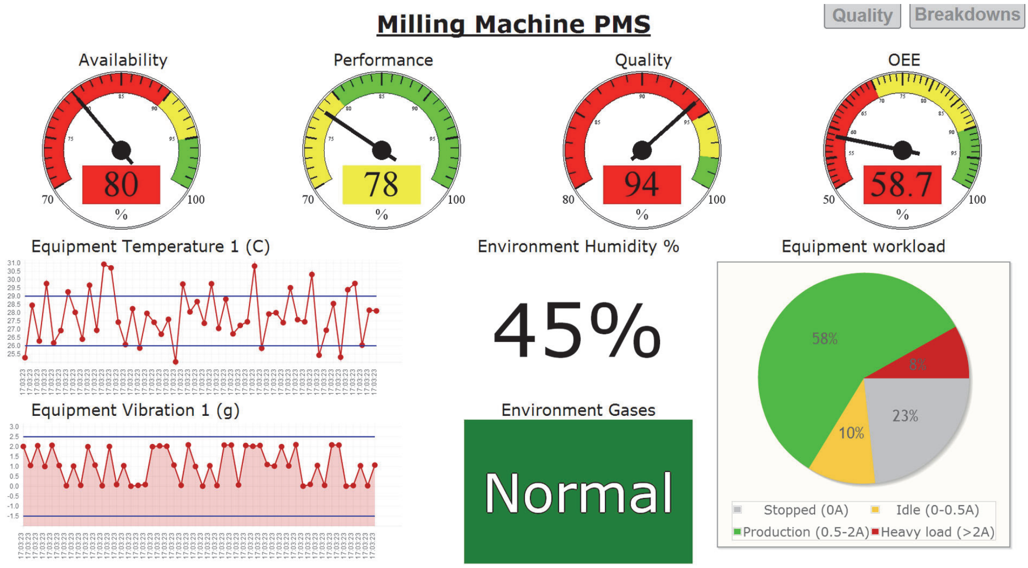

Fig. 10. Developed visual module for milling machine.

5. FURTHER RESEARCH

Advanced data analysis and prognostics methods should be researched, implemented, and tested to enhance proposed PMS for SMEs. Despite the fact that a variety of prognostic models has already been reported in technical literature, an effective prognostic methodology for industrial application has yet to be developed. As prognostics accuracy is a subject to stochastic processes that have not yet occurred, it is difficult to formulate clear systematic methodology for it. Because of that it is still primarily based on human expertise and knowledge through continuous monitoring and analysis of machine conditions.

The model for a group of machines and/or production cells should be tested (combined workshop overview) to help to balance the production and identify bottlenecks. Also different possibilities of integration with existing software (e.g., ERP, MRP) to share information should be analysed. And online training methods for users should be discussed.

6. CONCLUSIONS

Functionality of the core elements of the proposed PMS was described. Visual module for SMEs was designed and implemented in a production company that will help to get manufacturing benefits.

One of the main advantages is that the proposed production monitoring system is based on an open-source software and hardware to make it more affordable for users and support collaborative knowledge creation. Users have the possibility to change the functionality according to their needs. If more production enterprises/developers will implement and share open source production monitoring tools – it may help to simplify the next development to get even more competitive solution comparing to the commercial ones. All this may help to increase the number of companies who can start using advanced monitoring tools to increase shop floor visibility.

Depending on the production company type and organizational needs, PMS functionality may vary greatly. But the main principles described above may be used in different areas like additive manufacturing to even more advanced technology. Detailed information on operating resources and downtime analysis will result in higher utilization ratios. And collected data analysis will also help to find reasons of abnormal conditions. Indeed, development of advanced monitoring tools continues to be an interesting research topic and motivates to find new ways how to improve already existing solutions or develop new ones. This research could provide benefit to those who are going to design and implement production monitoring tools.

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Tootmise seiresüsteemi arendamine

Aleksei Snatkin, Tanel Eiskop, Kristo Karjust ja Jüri Majak

Artikli põhieesmärk on lihtsa, kuid tõhusa tootmise seiresüsteemi kontseptsiooni loomine ja visuaalse mooduli arendamine. Kirjeldatud põhiprintsiibid leiavad rakendust eri tootmisvaldkondades. Antud seiresüsteem annab täpse ülevaate tootmises toimuvast, lähtudes masina kasutamisest ja tootmisprotsessi stabiilsusest, võimaldades tekkivaid seisakuid ning kriitilisi olukordi õigeaegselt lahendada. Artiklis on kirjeldatud tootmisettevõtte jaoks arendatud seiresüsteemi visualiseerimise moodulit. Arendatud süsteem põhineb avatud lähtekoodiga tarkvaral. Tehtud uuring toob kasu neile, kes kavatsevad arendada tootmise seiresüsteeme ja vahendeid tootmisettevõtetele.

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5 Professional employment

Period	Organisation	Position
2015 - …	JELD-WEN Eesti AS	Category Manager
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6 Defended thesis

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7 Scientific projects

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01.01.2010-31.12.2013	Design of Materials and Structures with elastic and/or plastic anisotropy	ETF8485
01.01.2012-31.12.2014	Optimal design of composite and functional material structures, products and manufacturing processes	SF0140035s12
2015-2023	Resource efficient wooden structures and composites	TK146U03

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2014- 14th International Symposium “Topical Problems in the Field of Electrical and Power Engineering” (5 päeva)	Energia- ja geotehnika doktorikool II
2015- Closing Conference of the Project “Doctoral School of Energy and Geotechnology II” (5 päeva)	Energia- ja geotehnika doktorikool II

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Töötamise aeg	Tööandja nimetus	Ametikoht
2015 - …	JELD-WEN Eesti AS	Kategooriajuht
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2007 - 2009	Alfa Laval OÜ	Müügiinsener
2006 - 2007	ArcelorMittal Tallinn OÜ	Tootmise operaator/ kvaliteedispetisalist

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01.01.2010-31.12.2013	Materjalide ja konstruktsioonide optimeerimine arvestades elastset ja/või plastset anisotroopiat	ETF8485
01.01.2012-31.12.2014	Komposiit- ja funktsionaalsetest materjalidest konstruktsioonide, toodete ja tootmisprotsesside optimaalne projekteerimine	SF0140035s12
2015-2023	Ressursisäästlikud puit- ja komposiitkonstruktsioonid	TK146U03

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