Journal of Engineering Science and Technology
Vol. 12, No. 9 (2017) 2410 - 2425

PRODUCTION MONITORING SYSTEM WITH PREDICTIVE FUNCTIONALITY

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Abstract

The main objective of the current study is to analyse and develop production monitoring system (PMS) for small and medium enterprises (SME) with predictive functionality. The development of planned PMS covers design of hardware architecture, building data analysis and prediction tools. New tool wear forecast model has been developed. The proposed model extends traditional widely used models by introducing the effects of working regimes and multiple passes on tool/component wear.

Keywords: Artificial neural network, Manufacturing execution system, Predictive functionality, Production monitoring system.

1. Introduction

There are a number of initiatives existing in manufacturing industry under different names like "Industrial Internet" by General Electric or "Industry 4.0" particularly in Germany that promote a deployment of Cyber-Physical Systems, where physical processes are monitored and controlled by the embedded computers with feedback loops [1, 2].

Major challenges of such systems are to manage the substantial data volume that is generated, expensive IT infrastructure, lack of skilled employees and high implementation costs. The objective of this research is to offer a PMS that operates near real time and may be considered as an introduction towards the integration of new methodologies, offered by Cyber-Physical Systems [1, 3].

Large companies have more resources to implement new technologies than small and medium sized enterprises (SMEs), but they are not flexible in changing existing internal regulations, IT systems, security policies, etc. As a result of that

Nomenclatures

D	Work piece diameter (*mm*)
$F_{i,N}(\bar{x})$	Values of normalized output data
n	Spindle speed (min^{-1})
N_h	Number of neurons in hidden layer
N_{in}	Number of neurons in input layer
T_M	Maintenance time (*min*)
T_o	Initial life time (*min*)
T_R	Remaining life expectancy time (*min*)
$\bar{x}$	Vector if input variables
$X_{i,N}$	Values of normalized input data
V_{co}	Cutting speed (*m/min*)

Greek Symbols

Θ	Bias vectors of the three-layer perceptron network

Abbreviations

ANN	Artificial Neural Network
DOE	Design of Experiment
GUI	Graphical User Interface
ICT	Information and Communication Technologies
KPI	Key Performance Indicator
LLAP	Lightweight Local Automaton Protocol
MES	Manufacturing Execution System
MSE	Mean Square Error
SQL	Structured Query Language

current research focuses on increasing efficiencies in SMEs. The reduction in hardware price and extensive use of open-source software has the potential to boost implementation of different PMS, decreasing the high investment and implementation costs.

From authors' point of view, the one of the main tasks of a PMS is to assist operators to respond timely to the events that may affect the desired results [4, 5]. It can be seen as a part of Manufacturing Execution System (MES) [6] by having the same functions of data analysis and collection from the workshop.

PMS development is a multidisciplinary research that requires expertise in electrical engineering, material science, ICT, optimization, data mining, statistics and other disciplines. Definitely most of the companies do not have enough resources and time to develop an advanced production monitoring system from scratch. That is why a simple structure of a PMS is offered, based on easily obtainable low cost components, supported by a graphical user interface (GUI) visualizing relevant key performance indicators (KPI) for the enterprise [7, 8] and forecast module.

The amount of data to be processed is increasing gradually due to real time monitoring capabilities. These challenges can be handled by the Big Data covering large data collection and analysis techniques [9]. In described PMS data processing and storage capabilities are limited, therefore the data processing should be prioritized and a reasonable number of sampling points selected in advance. In order to form a unified picture, data from different sources may be combined and multi sensor data fusion applied [10].

The data analysis system should be self-learning to automatically update recommended set points. Facilitating the integration of artificial intelligence tools like artificial neural network (ANN) allows the system to be trained to predict output data according the new inputs [11]. Web based interface and online storage provides a lot of opportunities for PMS, but may bring security risks (e.g., capture of production data) [12]. Even though PMS is not adjusting production settings directly, but only advices to make changes that mitigates the risks of remote production disruption, it still participates in decision making. Thus, the data security policies (e.g., event logs, data encrypting, and system privileges) should be implemented in companies allowing remote access to their PMS. The collected data needs to be analysed to retrieve valuable information. A number of probability distributions have been proposed for prediction of the tool/component life, e.g., normal distribution, lognormal, inverse Gaussian, Bernstein, Gamma, exponential, Weibull [13]. These distributions based stochastic models can be considered as some alternatives for deterministic Taylor's extended model [14].

Application of advanced ICT allows to design PMS with cloud infrastructure, web-based interface and open source technologies [15-19]. In [15] and [16] the automatic cutting optimisation and tool wear and maintenance issues are studied, respectively. In [15] the optimisation based lifespan model considering multiple cutting tools and strategies is presented. In [17] the visualisation tools and cloud-assisted industrial cyber-physical systems are described. In [18] semantic web technologies to support the interoperability are introduced for solving the integration and data fusion problems between enterprise and control systems. In [19] the Virtual Factory approach is applied for discrete event simulation in production monitoring and simulation.

It should be pointed out that the Taylor and Taylor extended tool life-span models are still one of the most widely used models despite extensive research in this area during the last years [20]. In [13, 21-26] the deterministic models are proposed for tool/component life modelling. The detailed analysis of various lifespan models is performed in [13], where several shortcomings of the deterministic models are pointed out. Actually, 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 [13, 20].

A number of different solutions exist on the market under different definitions that may be described as a PMS. Most of these systems are commercial or custom made solutions for companies' internal use. In contrast, PMS described in this paper promotes collaboration in development of a cost-effective PMS, as it is based on an open source hardware and software and can be implemented to the company, depending on the actual need for measurement of different KPI's [27]. At the same time, the majority of existing systems, even commercial ones, have limited prognosis tools.

An aim of the current study is to develop PMS with real time monitoring capabilities, predictive functionality and web based responsible user interface.

The tool wear forecast model proposed cover the effects of multiple passes and different working regimes, which are not commonly included in tool life modeling [20-25]. Modern ICT tools including cloud infrastructure, web-based responsive user interface and artificial intelligence are incorporated.

2. Development of PMS for SME

For prototyping PMS, different types of data had to be collected such as a current, temperature, light intensity, humidity, acceleration, etc. The main functional requirements for PMS developed can be outlined as:

- Contain sensor system for measurement of selected basic characteristics
- Contain software tools for data processing, analysis and storing;
- Include web-based responsive user interface;
- Include forecast module;
    - Extreme working conditions should be covered (high vibrations, temperature, etc.);
    - Multiple passes should be covered (one tool/component may be used partial times in different working regimes);
- Provide capability for real time monitoring.

The following additional criteria should be also considered in design of PMS:

- Low power consumption;
- Portable -compact and interchangeable parts;
- Affordability -preferably based on open-source hardware;
- Possibility to increase storage capacity;
- Connectivity -wireless communication and easy integration with existing systems.

This chapter contain descriptions of the main subtasks of the proposed PMS. However, it seems reasonable to introduce first the conceptual scheme including process parameters considered, factors used for determining extreme regimes, data flow and applied tools (ANN).

2.1. Conceptual scheme

It can be seen from Fig. 1 that 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 scheme shown in Fig. 1 can be covered by the following three basic subtasks:

- development hardware prototype model for data acquisition,
- development of analytical tool life prediction model covering the effect of the process parameters and working regimes,
- development of ANN model for describing the dependence of the current, temperature and vibrations on processing parameters.

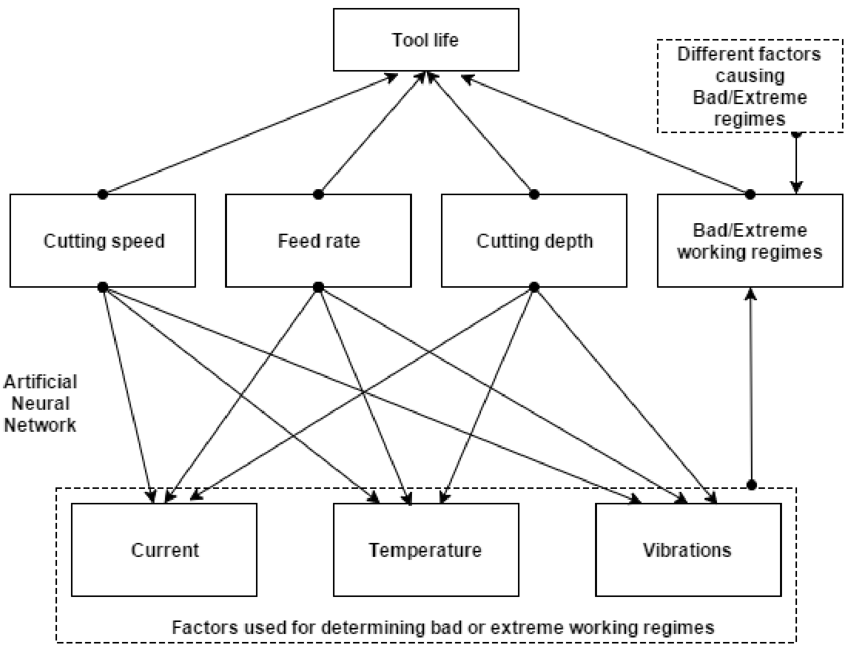

Fig. 1. Conceptual scheme.

These basic subtasks are described in details in the following Sections.

2.2. Hardware prototype model for data collection

The monitoring system developed has been implemented on DYNA MECH EM3116 milling machine in the laboratory of Tallinn University of Technology. Currently the implementation of the PMS system is in progress in the following two SME-s: Flexa Eesti OÜ and Sumar OÜ (measured quantities: cutting tool temperature, humidity, production meters, and visual defects of material). These two SME-s are working in area of machinery.

First at all it is correct to outline what data and where were measured:

- Current-current sensor was installed in the electrical cabinet of the machine on the main cable;
- Temperature-tool-work thermocouple was used in temperature measurements during metal cutting of St37-3 carbon steel. Entire tool was as the one part of the thermocouple and the work piece as the other part;
- Vibrations-a vibration sensor was installed on the spindle housing.

Based on criteria introduced above, the decision was made to use an Arduino Leonardo microcontroller together with a Raspberry Pi single board computer that is low-cost and easily available hardware on the market. The Arduino controllers are responsible for collecting the data from the sensors and sending it through wireless XRF module to Raspberry Pi computers. The controllers are programmed in the open source Arduino Software (IDE), which uses a simplified version of C++ language. For wireless data communication LLAP (lightweight local automation protocol) protocol is used. Each Arduino had possibility to save data locally on a SD card for backup. The Python coding language is used by the Raspberry PI to receive and save to local SQL database and also upload data to a remote server. PHP coding is employed to set up the server for Operator's GUI interface is running on a web server installed on the Raspberry Pi. Extensive calculations are handled on a remote server.

The communication between microcontrollers and single board computers with separated databases that send data to one common cloud server was tested (Fig. 2).

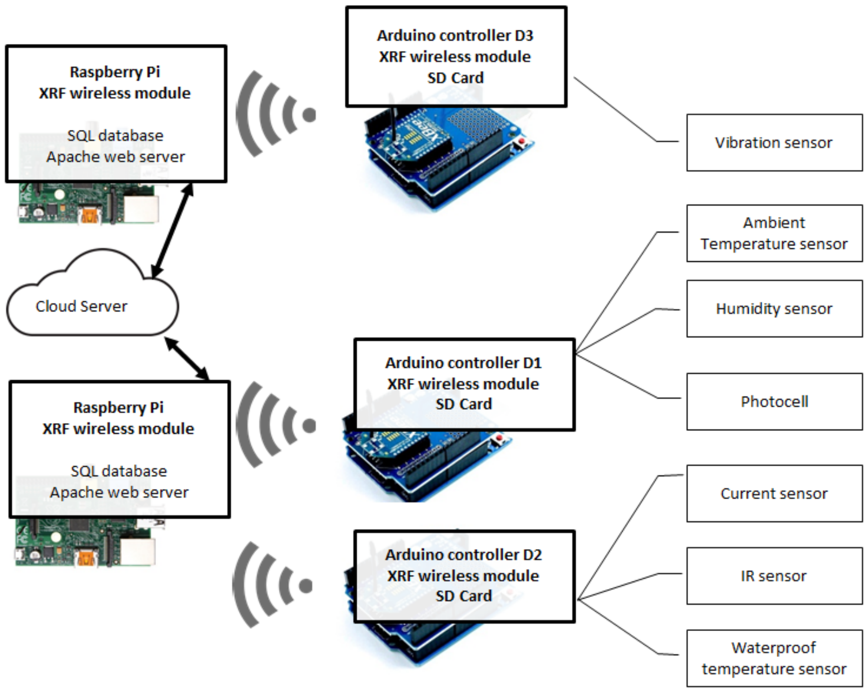

Fig. 2. Proposed hardware architecture.

2.3. ANN model for vibrations, temperature and current

Let us proceed from the conceptual scheme shown in Section 2.1 (Fig. 1). The following input and output data are considered for ANN model:

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

Development and exploitation of the ANN model is shown in Fig. 3. Thousands of data measured during real time monitoring process have been validated in regard to consistency and range. The non-consistent data, also data out of predefined range were deleted (due to packet loss, node failures, etc.). Despite to real time monitoring capabilities the data cannot be stored continuously. For that reason, the time intervals between data measurement/storage are introduced. Furthermore, in such a manner the capacity of the dataset can be kept in reasonable limits. Note that the selection of input and output data is not shown as first step of pre-processing in Fig. 3, since the collected dataset may include model dataset as subset. Thus, the data filtering is performed for all data collected, but certain characteristics are selected as variables of the prediction model developed.

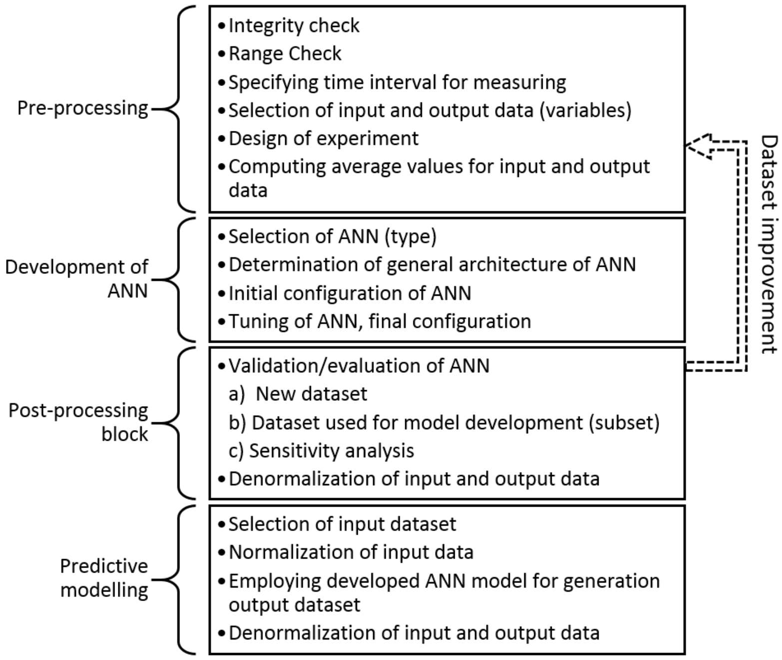

Fig. 3. Development and exploitation of ANN model.

Next step is design of experiment (DOE). From theoretical point of view here are a number of DOE methodologies available (Taguchi design, central composite design, full factorial design, d-optimality criteria, etc.), also opportunities for selection of input dataset. Based on the practical considerations herein has been selected full factorial design and relatively small number of levels for design variables (3 for rotational speed, 4 for cutting depth and feed rate, see Table 1). Full factorial design provides high accuracy but is too expensive if large number of levels, which are considered for design variables. The numbers of reconfigurations of the machine setups in manufacturing processes are needed to be kept reasonable. Real time monitoring of the manufacturing process provide thousands of results for each point of selected dataset. The average values of the "cleaned" and filtered data have been computed and used in further modelling. Thus, a hundred thousand of repetitive experimental data are covered by dataset with capacity of 48. In Table 1 are shown the values of the levels used for input data. The full factorial design of experiment is applied using 3 levels for spindle speed and 4 levels for cutting depth and feed rate.

Table 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

Last step of the data preparation for modelling is normalization of the input and output data by use of the following formulas:

$$X_{i,N} = \frac{x_i - x_{i,\min}}{x_{i,\max} - x_{i,\min}}, \tag{1}$$

$$F_{i,N}(\bar{x}) = \frac{f_i(\bar{x}) - f_{i,\min}(\bar{x})}{f_{i,\max}(\bar{x}) - f_{i,\min}(\bar{x})}. \tag{2}$$

In Eqs. (1) and (2) $\bar{x}$ is a vector of input variables, x_i and f_i stand for input and output variables, respectively. The normalized input and output variables are denoted by $X_{i,N}$ and $F_{i,N}(\bar{x})$, respectively. The values of normalized input data $X_{i,N}$ remains in range of {0,1}, but the value of the normalized output data may exceed slightly limits of the range {0,1}, since the maximum and minimum values of the output data are as rule the estimates for the upper/lower bounds rather than the exact values of the upper/lower bounds.

A number of mathematical models are available in literature for response modelling: linear and nonlinear regression, kriging, artificial neural networks, etc. Herein, the back-propagation ANN is employed for modelling the relations between input and output data. No specific rules for an appropriate 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 approximation of different functions [28]. 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 [29]. In current study the following formulas are considered to involve the capacity of the training data [28]:

$$N_h = (N_{in} + \sqrt{N_{tr}})/L, \tag{3}$$

$$N_h = C(N_{tr}/(N_{in}\log(N_{tr}))^{1/2}. \tag{4}$$

In Eq. (3) and (4) N_h, N_{in}, stand for number of neurons in hidden and input layers, respectively. A number of hidden layers and the capacity of the training data are denoted by L and N_{tr}, respectively. Equation (3) is used for determining the starting point and the number of hidden layers is increased up to upper bound set by the right hand side of Eq. (4). The tuning process of the ANN has been interrupted if the accuracy is not improved by further increasing the number of neurons. In the current study the hyperbolic tangent sigmoid and linear transfer functions were used in hidden and output layers, respectively.

In the algorithm proposed three subtasks are considered for validation of the ANN model developed. First the accuracy of the model is tested using two types of data points: points used in model development and some few new points. In most cases it is not meaningful to consider large number of data points for testing, but include most data for model development (critical applications covering medicine, space applications, etc. can be considered as exceptions). Figure 4 shows the values of the mean square error (MSE) for temperature in the case of stainless steel (MATLAB based solution).

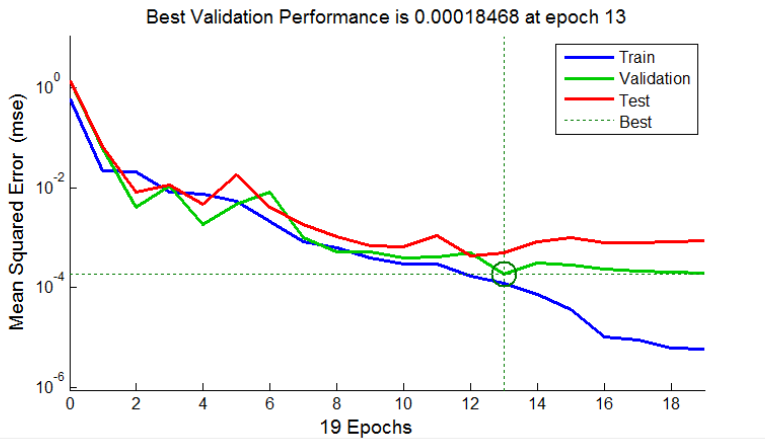

Fig. 4. The mean square for temperature.

Note that the response surface corresponding to ANN model does not contain necessarily exact values of the objective function obtained for to test data, but these values of objective function are used for building of response surface by minimizing MSE.

The last subtask of the ANN model validation contains sensitivity analysis. The output of the three-layer perceptron network considered can be evaluated as

$$Y = G_2(W_2 G_1(W_1 X + \Theta_1) + \Theta_2)\,. \tag{5}$$

In Eq. (5) X is input vector, Y is output vector, W_1, W_2 and Θ_1, Θ_2 stand for weight matrices and bias vectors, respectively. The transfer functions in the hidden and output layers are denoted by G_1 and G_2, respectively. The sensitivity matrix S can be computed as a gradient of the output vector Y as

$$S = \frac{\partial Y}{\partial X} = \frac{\partial F_2}{\partial Z_2} W_2 \frac{\partial F_1}{\partial Z_1} W_{1,} \tag{6}$$

where

$$Z_1 = W_1 X + \Theta_1 ,$$

$$Z_2 = W_2 G_1(Z_1) + \Theta_2 . \tag{7}$$

The sensitivity analysis performed confirm that the values of sensitivities with respect design variables remain moderate, i.e., the solution obtained is robust.

The ANN model developed allows predicting the values of the temperature, current and vibrations for desired input dataset remaining in design space. The obtained results are first de-normalized and then used as input data in tool life-span forecast model. The detailed numerical results and model validation data will be given in Section 3.

2.4. Tool life-span forecast model

Herein, the main attention is paid to minimizing maintenance time of the machine tools which depends on type and quality of materials and equipment used, products processed, vibrations, temperature, working regimes, etc. Since wearing of the tools/components depends on a number of counteracting factors listed above, unique approach for estimating aging seems here not to be available.

First, it is reasonable to point out main features of the proposed tool life-span forecast model, also to explain how it differs from widely used models.

Let start from simplest tool life estimate (8), which hold good for fixed values of process parameters and standard exploitation conditions

$$T_R = T_0 + T_{used} . \tag{8}$$

In (8) 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 tool, respectively.

In the case of widely used models the tool/component life is given as a function of process parameters, but the effects of extreme exploitation conditions (due to vibrations etc.) and multiple passes are most commonly omitted [21-25]. For example, in the case of traditional extended Taylor model the tool life is estimated as

$$T_{Taylor} = \frac{C}{(S_{cut\_speed})^{1/n}(f_{feed\_rate})^{q}(d_{cutting\_depth})^{r}} , \tag{9}$$

where L_{Taylor} is expected life time of the tool, C, n, q, and r are constants and S_{cut_speed}, f_{feed_rate} and $d_{cutting\_depth}$ stand for the cutting speed, feed rate and cutting depth, respectively. In [21, 22] and [22-25] the tool/component life dependence on process parameters is modelled by applying regression and ANN models, respectively.

In the proposed tool life forecast model

$$T_R = T_0 - \sum_{I=1}^{k} T^I S^I_{coeff} V^I_{coeff} C^I_{coeff} , \tag{10}$$

the effects of extreme exploitation conditions are considered through the vibration, temperature and current coefficients

$$V^I_{coeff} = \frac{V^I}{V_0^{vibration}}, S^I_{coeff} = \frac{t^I}{t_0^{temperature}}, C^I_{coeff} = \frac{C^I}{C_0^{current}}, \tag{11}$$

and the effects of the multiple passes are considered through summation over time intervals T^I. The effect of process parameters on tool life is considered in proposed model, Eq. (10), through the values of T^I by applying extended Taylor model, Eq. (9). In Eq. (11) V^I, t^I, C^I stand for the actual values of the vibrations, temperature and current in the time interval I and $V_0^{vibration}$, $t_0^{temperature}$, $C_0^{current}$ for predefined 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. The discrete values for the vibration, temperature and current implementing the working regimes are introduced as

$$V^I = \begin{cases} V_0^{vibration} & if \quad V_{avg} \le V_0 \\ V_1 & if \quad V_{avg} \in (V_0; V_1] \\ \ldots & \ldots \quad \ldots \\ V_M & if \quad V_{avg} \in (V_{M-1}; V_M] \end{cases}, \tag{12}$$

$$t^I = \begin{cases} t_0^{temperature} & if \quad t_{avg} \le t_0 \\ t_1 & if \quad t_{avg} \in (t_0; t_1] \\ \ldots & \ldots \quad \ldots \\ t_M & if \quad t_{avg} \in (t_{M-1}; t_M] \end{cases}, \tag{13}$$

$$C^I = \begin{cases} 0 & if \quad C_{avg} \le C_{busywork} \\ C_0^{current} & if \quad C_{avg} \in (C_{busywork}; C_0] \\ \ldots & \ldots \quad \ldots \\ C_M & if \quad C_{avg} \in (C_{M-1} C_M] \end{cases}. \tag{14}$$

The regime with low vibration value not exceeding V_o 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 $i = 1, \ldots .M$ 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 $t \le t_o$, etc.). The decisions for determining the regimes are made on base of the average values of the parameters.

In the following the behaviour of the discrete variables V^I_{coeff} 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 Eqs. (11) and (12) that the value of the coefficient $L^I_{vibr} \equiv 1$. Due to increasing values of the V_i ($i=1,...M$), the corresponding values of the coefficient V^I_{coeff} are increasing, see Eqs. (11) and 12, and thus satisfy the condition $V^I_{coeff} > 1$. In practice it means the 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 $C^I_{coeff} = 0$, Eqs. (11) and (13).

Such an approach is introduced due to the fact that in a real manufacturing process the values of the process parameters are varying in certain range (class, domain) and the current intensity has not unique value even for busy work. These changes of process parameters may be caused by a number of factors not included in the model.

Due to the presence of integer and discrete valued parameters the traditional gradient based optimization algorithms are not applicable for minimization of the maintenance time. Current study is focused on development of prediction tools. However, the hybrid genetic algorithm based global optimization techniques, developed by workgroup for wide class engineering problems [30-34], can be adopted for particular problem considered, i.e., for minimization of the maintenance time.

3. Results and discussion

Let start from ANN model validation. The ANOVA analysis was performed on the experimental data with aim to estimate the influence of the rotational 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 2 shows the computed p-values for all factors considered.

Table 2. 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 2 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.

The ANN has been built on dataset of capacity of 48, These 48 values of the vibration, temperature and current are computed as average values of several hundred thousand real time monitoring data (see details in Section 2.3) using 1000-2000 measured values for each point. In Table 3 is given sample dataset with capacity of 16 (the value of the rotational speed is fixed).

The remaining 32 data points correspond to the values of the rotational speed 400 and 500 min^{-1}, where the values of the cutting depth and feed rate are varied similarly to Table 3.

Table 3. Sample dataset of averaged values (used for composing ANN model, where rotational speed is fixed).

Rotational speed (min^{-1})	Cutting depth (mm)	Feed rate (mm/min)	Vibration 1g (9,8 m/s^2) = 100	Temp. (°C)	Current (A)
300	0.5	50	95.39	32.66	6.22
300	0.5	80	95.60	32.64	6.24
300	0.5	120	95.89	32.64	6.24
300	0.5	150	95.83	32.63	6.24
300	1	50	95.78	32.55	6.27
300	1	80	95.86	32.55	6.26
300	1	120	95.82	32.56	6.40
300	1	150	95.97	32.56	6.41
300	1.5	50	95.85	32.63	6.38
300	1.5	80	95.61	32.69	6.49
300	1.5	120	95.63	32.74	6.70
300	1.5	150	95.44	32.80	6.68
300	2	50	94.16	32.85	6.53
300	2	80	95.36	32.88	6.78
300	2	120	95.32	32.94	6.95
300	2	150	95.33	32.98	7.00

Note that there are not available general rules for defining working regimes, since working regimes depend strongly on particular problem considered. In the case of considered problem two working regimes for vibrations and temperature and three working regimes for current are used. The first regime is defined from consideration that in the case this regime the vibrations, temperature and current (here second regime for current, since first regime correspond for busywork) have not significant impact on tool life (up to 3%), i.e., first regime for vibration and temperature and second regime for current correspond to normal exploitation conditions. The second regimes in (12)-(14) have been defined so that the max value of the vibrations, temperature and current does not exceed 20% of its maximal value for first regime. It has been observed that in the case of the current problem there is not justified to apply extreme regimes for all three factors simultaneously, even if the measured values belong to extreme regimes for all factors, since such an approach lead to overestimating the tool wear rate. Thus, in the case of considered problem the extreme regimes can be applied up to two factors which measured values exceed limits of the first (standard) regime by higher percentage.

Obviously, the working regimes need set up/tuning for each particular problem considered. Also, the working regimes can be determined based on measured or modelled (ANN) values of selected key factors (for current problem vibrations, temperature and current).

4. Conclusion

The open source software and low cost hardware based PMS with predictive functionality has been developed for SMEs.

Main features of the proposed PMS are the following:

- It contains forecast module;
- It contains web based responsive user interface;
- It provides real time monitoring capability;
- The analytical tool life forecast model introduced covers the extreme working conditions and multiple passes.

Despite to new capabilities here are also certain complexities with application of the proposed systems like determining working regimes (data corresponding to extreme working regimes are rather “abnormal”, and their acquiring is time consuming). The future study of the research group is related with stochastic prognosis models, analysis and comparison of different deterministic and stochastic models, design optimization based on determining optimal values of the process parameters.

Acknowledgment

This research was supported by Innovative Manufacturing Engineering Systems Competence Centre IMECC (supported by Enterprise Estonia and co-financed by the European Union Regional Development Fund, project EU48685); Estonian Centre of Excellence in Zero Energy and Resource Efficient Smart Buildings and Districts, ZEBE, grant TK146 funded by the European Regional Development Fund; Estonian Research Council grant PUT1300.

References

1. Lee, J.; Bagheri, B.; and Kao, H.A. (2015). Cyber physical systems architecture for industry 4.0-based manufacturing systems. *Manufacturing Letters*, 3, 18-23.
2. Lee, E.A. (2006). Cyber-physical systems -are computing foundations adequate? *NSF Workshop on Cyber-Physical Systems: Research Motivation, Techniques and Roadmap*, 16-17 October, Austin, Texas, USA.
3. Monostori, L. (2014). Cyber-physical production systems: roots, expectations and R&D challenges. *Procedia CIRP*, 17, 9-13.
4. Snatkin, A.; Karjust, K.; Majak, J.; Aruväli, T.; and Eiskop, T. (2013). Real time production monitoring system in SME. *Estonian Journal of Engineering*, 19, 62-75.

5. Karjust, K.; Küttner, R.; and Pääsuke, K. (2010). Adaptive web based quotation generic module for SMEs. *Proceedings of 7th International Conference of DAAAM Baltic Industrial Engineering*, Tallinn University of Technology Press, Estonia, 375-380.
6. Saenz de Ugarte, B.; Ariba, A.; and Pellerin, R. (2009). Manufacturing execution system -a literature review. *Production Planning and Control*, 20, 525-539.
7. Karjust, K.; Pohlak, M.; and Majak, J. (2010). Technology route planning of large composite parts. *International Journal of Material Forming*, 3(1), 631-634.
8. Kaganski, S.; Snatkin, A.; Paavel, M.; and Karjust, K. (2013). Selecting the right KPIs for SMEs production with the support of PMS and PLM. *International Journal of Research in Social Sciences*, 1(3), 69 -76.
9. Kambatla, K.; Kollias, G.; Kumar, V.; and Grama, A. (2014). Trends in big data analytics. *Journal of Parallel and Distributed Computing*, 74(7), 2561-2573.
10. Khaleghi, B.; Khamis, A.; Karray, F.O.; and Razavi, S.N. (2013). Multisensor data fusion: A review of the state-of-the-art. *Information Fusion*, 14, 28-44.
11. Bonissone, P.; Goebel, K.; and Chen, Y.T. (2012). Predicting wet-end web breakage in paper mills. *Proceedings of AAAI Spring Symposium*, March, Stanford, California, USA.
12. Gosain, A.; and Arora A. (2015). Security issues in data warehouse: A Systematic review. *Procedia Computer Science*, 48, 149-157.
13. Vagnorius, Z. (2010). *Reliability of Metal Cutting Tools: Stochastic Tool Life Modelling and Optimization of Tool Replacement Time*. PhD Thesis, Norwegian University of Science and Technology, Trondheim.
14. Karandikar, J.M.; Abbas, A.E.; and Schmitz T.L. (2014). Tool life prediction using Bayesian updating. Part 2: Turning tool life using a Markov Chain Monte Carlo approach. *Precision Engineering*, 38, 18-27.
15. Tapoglou, N.; Mehnen, J.; Vlachou, A.; Doukas, M.; Milas, N.; and Mourtzis, D. (2015). Cloud-based platform for optimal machining parameter selection based on function blocks and real time monitoring. *Journal of Manufacturing Science and Engineering*, 137 (4).
16. Mourtzis, D.; Vlachou, E.; Milas, N.; and Xanthopoulos, N. (2016). A cloud-based approach for maintenance of machine tools and equipment based on shop-floor monitoring. *Procedia CIRP*, 41, 655-660.
17. Yue, X.; Cai, H.; Yan, H.; et al. (2015). Cloud-assisted industrial cyber-physical systems: An insight. *Microprocessors and Microsystems*, 39 (8), 1262-1270.
18. Kádár, B.; Terkaj, W.; and Sacco, M. (2013). Semantic virtual factory supporting interoperable modelling and evaluation of production systems. *CIRP Annals-Manufacturing Technology*, 62 (1), 443-446.
19. Terkaj, W.; Tolio T.; and Urgo, M. (2015). A virtual factory approach for in-situ simulation to support production and maintenance planning. *CIRP Annals-Manufacturing Technology*, 64 (1), 451-454.

20. Li, B. (2012). A review of tool wear estimation using theoretical analysis and numerical simulation technologies. *International Journal of Refractory Metals and Hard Materials*, 35, 143-151.
21. Attanasio, A.; Ceretti, E.; and Giardini, C. (2013). Analytical models for tool wear prediction during AISI 1045 turning operations. *Procedia CIRP*, 8, 218-223.
22. Suresh, R.; and Basavarajappa, S. (2014). Effect of process parameters on tool wear and surface roughness during turning of hardened steel with coated ceramic tool. *Procedia Material Science*, 5, 1405-1459.
23. Venkata Rao, K.; Murthy, B.S.N.; and Mohan Rao, N. (2014). Prediction of cutting tool wear, surface roughness and vibration of work piece in boring of AISI 316 steel with artificial neural network. *Measurement*, 521, 63-70.
24. Xu, C.; Xu, T.; Zhu, Q.; and Zhang, H. (2011). Study of adaptive model parameter estimation for milling tool whear. *Strojniški Vestnik-Journal of Mechanical Engineering*, 57 (7-8), 568-578.
25. D'Addona, D.M.; Genna, S.; Leone, C.; and Matarazzo, D. (2016) Prediction of poly-methyl-methacrylate laser milling process characteristics based on neural networks and fuzzy data. *Procedia CIRP*, 41, 981-986.
26. Leone, C.; D'Addona, D.; and Teti, R. (2011). Tool wear modelling through regression analysis and intelligent methods for nickel base alloy machining. *CIRP Journal of Manufacturing Science and Technology*, 4, 327-331.
27. Heron, M.; Hanson, V.L.; and Ricketts, I. (2013). Open source and accessibility: advantages and limitation. *Journal of Interaction Science*, 1, 1-10.
28. Sheela, K.G.; and Deepa, S.N. (2013). Review of methods to fix number of hidden neurons in neural networks. *Mathematical Problems in Engineering*.
29. Hecht-Nielsen, R. (1989). Theory of the Back Propagation Neural Network. *Proceedings of the International Joint Conference on Neural Networks*, 1, 593-608.
30. Herranen, H.; Pabut, O.; Eerme, M.; Majak, J.; Pohlak, M.; Kers, J.; Saarna, M.; Allikas, G.; and Aruniit, A. (2011). Design and testing of sandwich structures with different core materials. *Journal of Materials Science of Kaunas Univ. of Technology*, 17(4), 1-6.
31. Majak, J.; and Pohlak, M. (2010). Decomposition method for solving optimal material orientation problems. *Composite Structures*, 92(8), 1839-1845.
32. Kers, J.; Majak, J.; Goljandin, D.; Gregor, A.; Malmstein, M.; and Vilsaar, K. (2010). Extremes of apparent and tap densities of recovered GFRP filler materials. *Composite Structures*, 92(9), 2097 -2101.
33. Majak, J.; and Pohlak, M. (2010). Optimal material orientation of linear and non-linear elastic 3D anisotropic materials. *Meccanica*, 45(5), 671-680.
34. Lellep, J.; and Majak, J. (2000). Nonlinear constitutive behavior of orthotropic materials. *Mechanics of Composite Materials*, 36, 261-266.