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INDUSTRIAL ENGINEERING

Production monitoring system design and implementation

Tanel Eiskop[a*], Aleksei Snatkin[b], Kristo Karjust[a], and Ernst Tungel[c]

[a] Department of Mechanical and Industrial Engineering, Tallinn University of Technology, Ehitajate tee 5, 19086 Tallinn, Estonia
[b] JELD-WEN Eesti AS, Arkna tee 1, 44317 Rakvere, Estonia
[c] Tartu College, Tallinn University of Technology, Ehitajate tee 5, 19086 Tallinn, Estonia

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Abstract. The aim of the current study was to develop a highly flexible and scalable modular real-time monitoring system with predictive capabilities. The main focus was on forecasting tool/component life-span. A two-stage model is proposed for predicting tool life-span. Based on real-time monitoring data a back-propagation artificial neural network model was developed and validated. The obtained response surfaces for vibrations, current, and temperature are utilized in an analytical tool wear forecast model.

Key words: production monitoring system, tool life modelling, ANN.

1. INTRODUCTION

The rapid development of microcontroller and micro-processor technologies, cloud computing, big data, and the emergence of the framework for Industry 4.0 have made the possibilities of small and medium-sized enterprises (SMEs) and micro-enterprises of using new emerging technologies in the operations management more accessible and feasible. The production monitoring system (PMS) can be considered as an integral part in moving towards an interconnected enterprise, laying the foundation for production environment, process, machine condition, personnel, and asset monitoring. Sensing the status of the processes and resources automatically enables quick insights into and timely reaction to disturbances, presents a baseline for quality and root cause analysis, predictive maintenance, and many other production improvement and optimization methodologies.

The PMS is a subsystem of the manufacturing execution system (MES). It concentrates on some of the same aspects as the MES such as data collection and acquisition, performance analysis, and process status monitoring [1]. At the same time the PMS is closely related to supervisory control and data acquisition (SCADA) systems, which originally provided operation and process control and monitoring functions but nowadays include reporting, scripting, performance analysis, and prognostic and integration capabilities [2–4].

The general aim of the research group is to design a scalable and highly configurable PMS for SMEs based on open-source technologies. However, the current study is focused on tool life modelling as one sub-task. The topics covering the conceptual design of the PMS, hardware selection/development, data collection and filtering, etc. are discussed in detail in previous papers of the workgroup [1,2] and are not repeated in detail herein.

In order to predict the need for maintenance of tools/components and provide higher safety, predictive modelling can be performed [5–9]. An overview of

[*] Corresponding author, taneleiskop@gmail.com

various tool life prediction models can be found in [5–12]. In [5] deterministic and stochastic models are compared and some shortcomings of the deterministic models are pointed out. In practice the process parameters fluctuate around setup values and the geometry and materials of the tools/components, also work-pieces, external conditions, etc. may vary. For that reason stochastic tool life prediction models are introduced in [5,8].

In the current study a new tool life prediction model covering the effects of multiple passes and harsh/extreme working regimes is introduced. The proposed model includes a stochastic term related to harsh/extreme working regimes.

2. GENERAL CONCEPT

A PMS is a system enabling enterprises to automatically acquire relevant data from production processes with an improved efficiency and consistency compared to manual data collection. A PMS should be able to measure the great majority of the variables that could in any shape or form influence the outcome of the production process (see Fig. 1).

In this study production environment (humidity, temperature, airflow, volatile organic compounds, gas content), process (process parameters, product tracking, process efficiency), machine condition (current, temperature, vibration, noise level), personnel, and asset monitoring (location, movements) are defined as the main focus areas for developing a PMS. Depending on the implementation, the configuration of the solution and sensing options may vary.

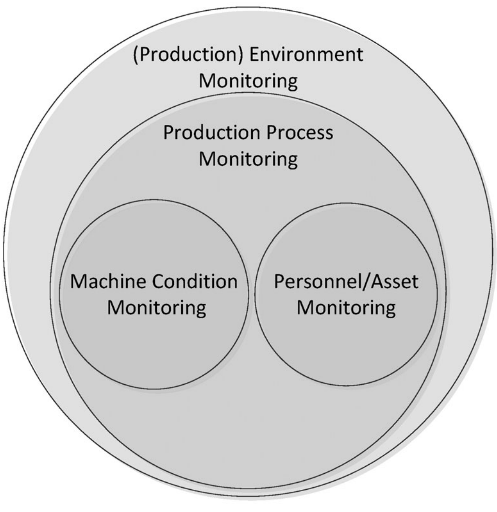

Fig. 1. PMS measurement modules.

2.1. Database design

A detailed description of the conceptual design of the considered PMS, as well as hardware design and data filtering is given in [1,2] and is omitted here for conciseness sake (selection of X-ray fluorescence (XRF) nodes, Arduino Leonardo, Raspberry Pi, etc.).

In analysing the requirements for the system designing, the data structure for the PMS of the following criteria was taken into account [13]:

1. Limited data transfer capability of the XRF nodes.
2. Limited computing power of the Arduino Leonardo.
3. Limitations of the Raspberry Pi data collection node.
4. Ability to configure the system based on the company needs and increase the number of nodes used with minimal effort.

The database structure, shown in Fig. 2, was derived for a particular company considering mainly the need to keep the tables with highest requests for recording and reading data as simple as possible to avoid sending/ receiving unnecessary information. Further testing must be conducted to determine the limits of the proposed database structure. The possibility of processing part of the sensor data on the sensor nodes should be considered for effective resource usage [14,15]. To minimize the data sent through the radio frequencies the nodes were set to send new information only in the event of change.

The model describes only the minimal data required for the system. It can be easily adapted based on individual or company needs.

2.2. Data analysis and predictive modelling

The following two-stage procedure was developed for modelling tool/component ageing:

– development of a mathematical model for the characterization of vibrations, temperature, and current;
– development of a discrete analytical life-span forecast model for the considered tools/components.

The values of vibrations, temperature and current can be employed for the detection of working regimes and for the building of a tool life-span forecast model.

2.2.1. Tool life-span forecast model

The tool life modelling was performed in order to predict the need for maintenance, to avoid injuries and breakdown of the tools or components, and to provide higher safety [5–12]. The tool life-span model proposed covers the effects of multiple passes and harsh/extreme working regimes. Its derivation process is illustrated in Fig. 3.

As it can be seen, the model development is performed starting from the simplest existing model and adding new features step by step.

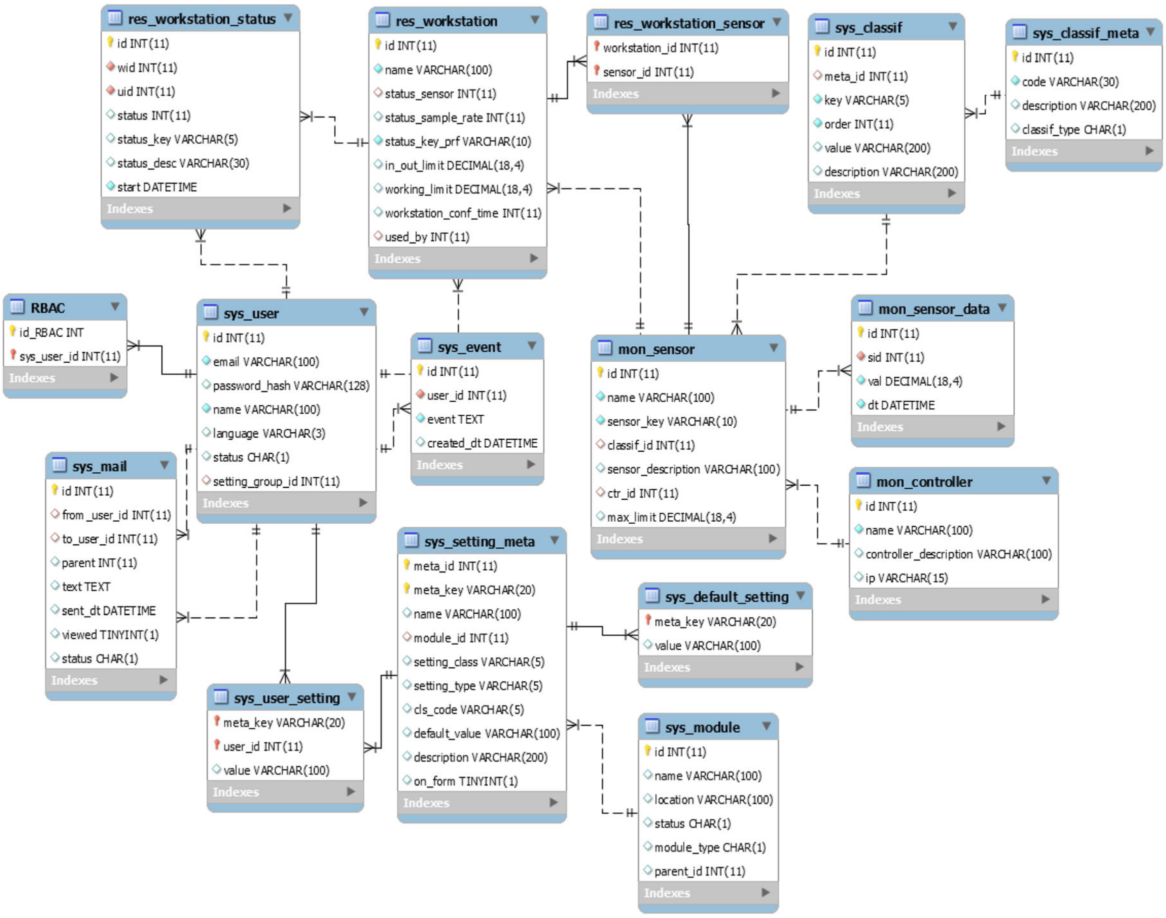

Fig. 2. Production monitoring system enhanced entity-relationship (EER) diagram.

The forecast model of tool wearing is proposed in the following form:

$$T_{\mathrm{R}} = T_0 - \sum_{I=1}^{k} T^{\mathrm{I}} L^{\mathrm{I}}_{\mathrm{proc\_par}} L^{\mathrm{I}}_{\mathrm{vibr}} L^{\mathrm{I}}_{\mathrm{temp}} L^{\mathrm{I}}_{\mathrm{current}} (1-\alpha), \qquad (1)$$

where T_0 and T_{R} stand for the initial and remaining life expectancy of the tool, T^{I} is the length of the Ith time interval, and $L^{\mathrm{I}}_{\mathrm{proc\_par}}$ is the tool life expectancy coefficient. The effect of harsh/extreme working regimes is introduced in the tool life model (1) through coefficients $L^{\mathrm{I}}_{\mathrm{vibr}}, L^{\mathrm{I}}_{\mathrm{temp}}$, and $L^{\mathrm{I}}_{\mathrm{current}}$ defined as

$$L^{\mathrm{I}}_{\mathrm{vibr}} = \frac{V^{\mathrm{I}}}{V_0}, \quad L^{\mathrm{I}}_{\mathrm{temp}} = \frac{t^{\mathrm{I}}}{t_0}, \quad L^{\mathrm{I}}_{\mathrm{current}} = \frac{C^{\mathrm{I}}}{C_0}, \qquad (2)$$

where $V^{\mathrm{I}}, t^{\mathrm{I}}$, and C^{I} stand for the actual values of the vibrations, temperature, and current in the time interval I and V_0, t_0, and C_0 for predefined values of the same variables corresponding to the normal/reference working regime. In the case of low vibrations corresponding to the normal regime $L^{\mathrm{I}}_{\mathrm{vibr}} = 1$. Similarly, $L^{\mathrm{I}}_{\mathrm{temp}} = 1$ and $L^{\mathrm{I}}_{\mathrm{current}} = 1$ for values of the temperatures and currents remaining in the range corresponding to the normal working regime. The working regimes are determined based on measured values of the vibration, temperature, and current for particular tools and materials. In the case of higher values of vibrations, temperature, and current corresponding to harsh or extreme working regimes the coefficients $L^{\mathrm{I}}_{\mathrm{vibr}}$, $L^{\mathrm{I}}_{\mathrm{temp}}$, and $L^{\mathrm{I}}_{\mathrm{current}}$ exceed the value 1, which corresponds in practice to higher wearing rates of the tool.

The tool life expectancy coefficient $L^{\mathrm{I}}_{\mathrm{proc\_par}}$ in (1) describes the effect of the cutting speed $(L^{\mathrm{I}}_{\mathrm{cut\_speed}})$, feed rate $(L^{\mathrm{I}}_{\mathrm{feed\_rate}})$, and cutting depth $(L^{\mathrm{I}}_{\mathrm{cut\_depth}})$ on the tool life and is introduced as

$$L_{\mathrm{proc\_par}} = \frac{L_{\mathrm{pp}}(S^0_{\mathrm{cut\_speed}}, f^0_{\mathrm{feed\_rate}}, D^0_{\mathrm{cut\_depth}})}{L_{\mathrm{pp}}(S^{\mathrm{actual}}_{\mathrm{cut\_speed}}, f^{\mathrm{actual}}_{\mathrm{feed\_rate}}, D^{\mathrm{actual}}_{\mathrm{cut\_depth}})}. \qquad (3)$$

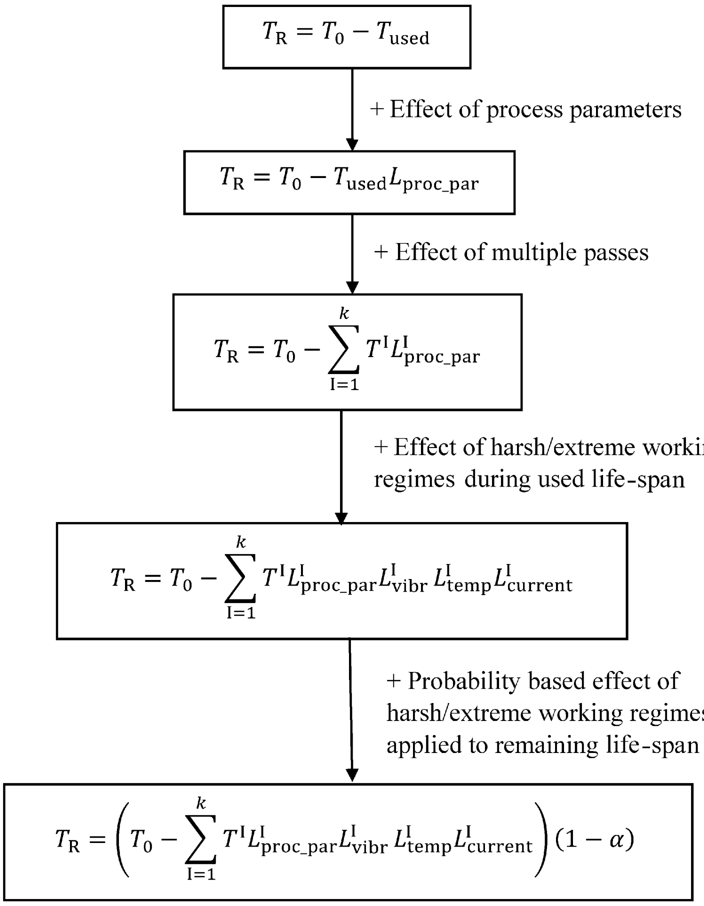

Fig. 3. Development process of the tool life-span model.

In (3) the reference values of the process parameters are denoted by index zero. The function $L_{pp}(S_{cut\_speed}, f_{feed\_rate}, D_{cut\_depth})$ in (3) is introduced in general form in order to cover a wide range of analytical and semi-analytical tool life-span prediction models. In the case of an extended Taylor tool life model the function L_{pp} takes the following form:

$$L_{pp} = L_{Taylor} = \frac{C}{(S_{cut\_speed})^{1/n}(f_{feed\_rate})^{q}(d_{cutting\_depth})^{r}}, \quad (4)$$

where L_{Taylor} is the expected life-span of the tool, and C, n, q, and r stand for constants. The function $L_{pp} = L_{pp}(S_{cut\_speed}, f_{feed\_rate}, D_{cut\_depth})$ can be modelled by applying nonlinear regression, artificial neural networks (ANN), etc. in the same way as done for tool wear in [7,8].

Finally, note that the tool life expectancy model (1) includes a stochastic term α representing the additional wearing caused by harsh/extreme working regimes occurring during the remaining life expectancy time of the tool. The component of the stochastic term α caused by higher values of vibrations during a harsh/extreme working regime can be computed as the product of the probability that a harsh/extreme regime occurs and the corresponding complementary vibrations are given in the normalized form

$$P(V_{be\_low} < V^{I}_{avg} \le V_{be\_up}) \frac{V^{I}_{avg} - V_0}{V_0}, \quad (5)$$

where V_{be_low} and V_{be_up} stand for lower and upper limits of the harsh/extreme working regime. In the case when several such regimes are defined, the summation should be performed over these regimes. The components of the stochastic term α caused by higher values of the temperature and current can be computed similarly to Eq. (5). Herein, the corresponding formulas are omitted for conciseness sake.

Note that in the case of a normal working regime the values of the process parameters are equal to the reference values:

$$V_{\mathrm{avg}}^{\mathrm{I}} \le V_0, t_{\mathrm{avg}}^{\mathrm{I}} \le t_0, C_{\mathrm{avg}}^{\mathrm{I}} \le C_0,$$
$$S_{\mathrm{cut\_speed}}^{\mathrm{I}} = S_{\mathrm{cut\_speed}}^{0}, \; f_{\mathrm{feed\_rate}}^{\mathrm{I}} = f_{\mathrm{feed\_rate}}^{0}, \qquad (6)$$
$$d_{\mathrm{cut\_depth}}^{\mathrm{I}} = d_{\mathrm{cut\_depth}}^{0}$$

and the proposed tool life expectancy model reduces to the well-known simplest model given as

$$T_{\mathrm{R}} = T_0 - T_{\mathrm{used}}. \qquad (7)$$

2.2.2. Modelling vibrations, temperature, and current

The cutting speed, cutting depth, and feed rate are considered as input data. Real-time data collection produces as rule thousands of repetitive results. For that reason, average values of the filtered data were utilized. The levels of the input data are given in Table 1.

A data set with the capacity of 48 was selected, including four levels for cutting depth and feed rate and three levels for spindle speed. The full factorial design of experiment (DOE) was performed. The acquired data were validated in regard to consistency and range. The missing and inaccurate values were deleted. The time intervals between data measurement and storage were introduced in order to keep the capacity of the data set within reasonable limits.

A mathematical model based on back-propagation ANN was developed. Both the input and output data are normalized in order to provide the same range of all variables. The ANN was configured (tuned) based on the accuracy and robustness of the model.

The following three subtasks for the evaluation of the ANN model were employed:
- testing the points used in the model,
- testing new points,
- sensitivity analysis of the model.

The performance of the solution is illustrated in Fig. 4.

Sensitivity analysis was performed as the final step of the ANN model validation. The output vector Y as a function of the input vector X can be computed for the ANN with one hidden layer as

$$Y = G_2(W_2 G_1(W_1 X + \Theta_1) + \Theta_2), \qquad (8)$$

where W_1, W_2, and Θ_1, Θ_2 denote weight matrices and bias vectors, respectively, and G_1 and G_2 are transfer functions in the hidden and output layers, respectively.

By computing the gradient of the output vector Y one obtains the sensitivity matrix as

$$S = \frac{\partial Y}{\partial X} = \frac{\partial G_2}{\partial Z_2} W_2 \frac{\partial G_1}{\partial Z_1} W_1, \qquad (9)$$

where

$$Z_1 = W_1 X + \Theta_1, Z_2 = W_2 G_1(Z_1) + \Theta_2. \qquad (10)$$

It was confirmed that the computed values of the sensitivities remain in a reasonable range with respect to the design variables. By employing the ANN model developed the values of the temperature, current, and vibrations can be determined in any data-point required (not outside the design space). The values of the temperature, current, and vibrations can be applied for determining the working regimes of the machine (equipment).

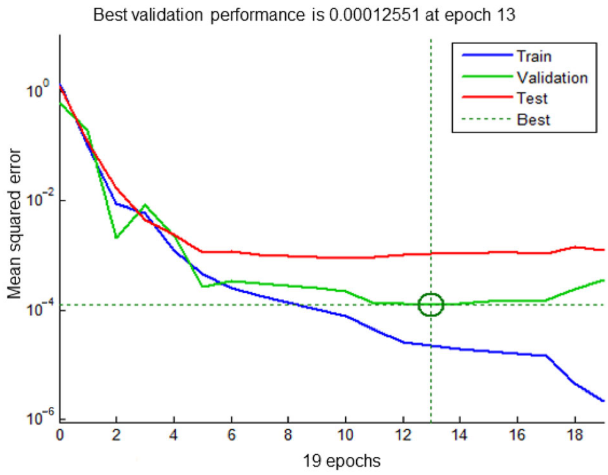

Fig. 4. The mean squared error of the temperature.

Table 1. Levels of the design variables

Rotational speed, 1/min	Cutting depth, mm	Feed rate, mm/min
300	0.5	50
400	1.0	80
500	1.5	120
	2.0	150

3. RESULTS AND DISCUSSION

The averaged measured values of the vibrations, cutting temperature, and current are shown in Table 2. Here the value of the cutting speed is fixed and the values of the cutting depth and feed rate are varied (one third of the total data obtained).

Table 2. Averaged measured values at a rotational speed of 300 1/min

Cutting depth, mm	Feed rate, mm/min	Vibration, 1 g	Temp., ºC	Current, A
0.5	50	95.39	142	6.22
0.5	80	95.60	150	6.24
0.5	120	95.89	159	6.24
0.5	150	95.83	165	6.24
1	50	95.78	160	6.27
1	80	95.86	164	6.26
1	120	95.82	168	6.40
1	150	95.97	179	6.41
1.5	50	95.85	180	6.38
1.5	80	95.61	180	6.49
1.5	120	95.63	181	6.70
1.5	150	95.44	182	6.68
2	50	94.16	182	6.53
2	80	95.36	183	6.78
2	120	95.32	188	6.95
2	150	95.33	197	7.00

To estimate the influence of the cutting speed, feed rate, and cutting depth on vibrations, temperature, and current, analysis of variance (ANOVA) was performed on the experimental data. The analysis was carried out at 95% level of confidence (i.e. significance 0.05). Table 3 presents the computed p-values for all factors considered.

All factors are significant for current, temperature, and z-component of the vibrations as their p-values are less than 0.05 (Table 3). The cutting depth is non-significant for the x and y components of the vibrations and the feed rate is non-significant for the y component of the vibrations.

In the tool wear forecast model, the function $L_{\mathrm{pp}}(S_{\mathrm{cut\_speed}}, f_{\mathrm{feed\_rate}}, D_{\mathrm{cut\_depth}}$ was implemented as an extended Taylor model. Certain differences of the proposed and widely used traditional approaches can be outlined as follows.

Table 3. Results of ANOVA: p-values

Factor	Rotational speed, 1/min	Feed rate, mm/min	Cutting depth, mm
Current	0.005	0.000	0.000
Temp.	0.000	0.000	0.000
Vibration, x-axis	0.024	0.037	0.405
Vibration, y-axis	0.003	0.057	0.906
Vibration, z-axis	0.000	0.000	0.008

– The traditional models like an extended Taylor model (see [8]) consider as a rule the effect of the processing parameters only for estimating tool life expectancy. In the current approach the effect of working regimes is incorporated.
– Most commonly, the tool life expectancy models allow the prediction tool of life as whole under certain exploitation conditions (values of process parameters, working regimes, etc.). The proposed concept and model allows additionally the estimation of the remaining tool life also for a partially used tool if the exploitation conditions during the used and forward time are known.
– The widely used simple models are commonly deterministic. The proposed model includes an uncertainty term.
– The life-span prediction model developed is based on the use of real-time monitoring data and is capable of taking into account the effects of working as well as particular materials, environment conditions, etc.

In the current study the proposed analysis model is used for machine tool wear analysis, but it can be applied/extended for wear analysis of a wide class of components.

4. CONCLUSIONS

A two-stage model was developed for predicting tool life-span. First, the ANN-based response surfaces were treated for modelling vibrations, temperature, and current. Next the tool life-span forecast model was developed.

The further study planned will be related to design optimization of tool maintenance time. The hybrid genetic algorithm based global optimization techniques, developed by the workgroup for a wide class of engineering problems [15–18], can be adopted for a particular problem considered.

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REFERENCES

1. Eiskop, T., Snatkin, A., Kõrgesaar, K., and Søren, J. Development and application of a holistic production monitoring system. In *Proceedings of the 9th International Conference of DAAAM Baltic Industrial Engineering* (Otto, T., ed.). Tallinn University of Technology, Tallinn, 2014, 85–91.
2. Snatkin, A., Eiskop, T., Karjust, K., and Majak, J. Production monitoring system development and modification. In *Proc. Estonian Acad. Sci.*, 2015, **64**, 567–580.
3. Sahno, J., Shevtshenko, E., and Karaulova, T. Framework for continuous improvement of production processes. *Inzinerine Ekonomika : Engineering Economics*, 2015, **26**(2), 169–180.
4. Karaulova, T., Poljantshikov, I., Shevtshenko, E., and Kramarenko, S. Fractal approach for manufacturing project managements. *Mechanics*, 2014, **20**, 352–359.
5. Vagnorius, Z. Reliability of Metal Cutting Tools: Stochastic Tool Life Modelling and Optimization of Tool Replacement Time. PhD Thesis, Norwegian University of Science and Technology, Trondheim, 2010.
6. Suresh, R. and Basavarajappa, S. Effect of process parameters on tool wear and surface roughness during turning of hardened steel with coated ceramic tool. *Procedia Material Science*, 2014, **5**, 1450–1459.
7. Attanasio, A., Ceretti, E., and Giardini, C. Analytical models for tool wear prediction during AISI 1045 turning operations. *Procedia CIRP*, 2013, **8**, 218–223.
8. Li, B. A review of tool wear estimation using theoretical analysis and numerical simulation technologies. *Int. J. Refract. Met. H.*, 2012, **35**,143–151.
9. Rao, K. V., Murthy, B. S. N., and Rao N. M. Prediction of cutting tool wear, surface roughness and vibration of work piece in boring of AISI 316 steel with artificial neural network. *Measurement*, 2014, **51**, 63–70.
10. D'Addona, D. M., Genna, S., Leone, C., and Matarazzo, D. Prediction of poly-methyl-methacrylate laser milling process characteristics based on neural networks and fuzzy data. *Procedia Cirp*, 2016, **41**, 981–986.
11. Xu, C., Xu, T., Zhu, Q., and Zhang, H. Study of adaptive model parameter estimation for milling tool wear. *J. Mech. Eng.*, 2011, **57**(7–8), 568–578.
12. Leone, C., D'Addona, D., and Teti, R. Tool wear modelling through regression analysis and intelligent methods for nickel base alloy machining. *CIRP-JMST*, 2011, **4**, 327–331.
13. Davidson, L. and Moss, J. M. *Pro SQL Server 2012: Relational Database Implementation*. Apress, Berkely, CA, USA, 2012.
14. Leo, M., Distante, C., Bernabei, M., and Persaud, K. An efficient approach for preprocessing data from a large-scale chemical sensor array. *Sensors (Basel)*, 2014, **14**, 17786–17806.
15. Majak, J., Pohlak, M., Eerme, M., and Velsker, T. Design of car frontal protection system using neural networks and genetic algorithm. *Mechanika*, 2012, **4**, 453–460.
16. Karjust, K., Pohlak, M., and Majak, J. Technology route planning of large composite parts. *International Journal of Material Forming*, 2010, **3**, 631–634.
17. Majak, J. and Pohlak, M. Decomposition method for solving optimal material orientation problems. *Compos. Struct.*, 2010, **92**, 1839–1845.
18. Herranen, H., Pabut, O., Eerme, M., Majak, J., Polak, M., Kers, J., et al. Design and testing of sandwich structures with different core materials. *Mater. Sci. – Medzg.*, 2011, **18**, 45–50.

Tootmise seiresüsteemi projekteerimine

Tanel Eiskop, Aleksei Snatkin, Kristo Karjust ja Ernst Tungel

On käsitletud modulaarsete reaalajas töötavate tootmise seiresüsteemide projekteerimist. Loodava seiresüsteemi ühe olulise omadusena võib nimetada prognoosimise mooduli kaasamist. Antud artiklis on põhitähelepanu koondatud tööriista/komponendi kasutusaja prognoosimisele. Väljatöötatud kaheastmeline arendusmudel sisaldab tehisnärvivõrkude mudelit võnkumiste, temperatuuri ja voolutugevuse mõju hindamiseks tööriista kasutusajale ning analüütilist tööriista kasutusaja prognoosimise mudelit, mis arvestab töörežiimide mõju.