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Manufacturing Process Optimization and Tool Condition Monitoring in Mechanical Engineering

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Abstract. The optimization of manufacturing and production processes with various computer software is essential these days. Solutions on the market allow us to optimize and improve our manufacturing and production processes; one of the most popular software is called Tecnomatrix, which is described in this paper. Tool condition monitoring is a vital part of the manufacturing process in the industry. It requires continuous measurement of the wear of the cutting tool edges to improve the surface quality of the work piece and maintain productivity. Multiple methods are available for the determination of the actual condition of the cutting tool. Vibration diagnostics and acoustic methods are included in this paper. These methods are simple, it requires only high sensitive sensors, microphones, and data acquisition unit to gather the vibration signal and make signal improvement. Extended Taylor equation is applied for tool edge wear ratio. Labview and Matlab software are applied for the measurement and the digital signal processing. Machine learning method with artificial neural network is for the detection and prediction of the edge wear to estimate the remaining useful lifetime (RUL) of the tool.

Keywords: Tecnomatix, plant simulation, tool, wear, diagnosis, machine learning

Introduction

Modern manufacturing techniques and softwares play crucial rule in the industrial processes. GraphIT products include well-known and popular CAD / CAM / CAE and PLM software such as Solid Edge (CAD), NX (CAD / CAM / CAE), Teamcenter (PLM), Tecnomatix. The product range of Siemens Tecnomatix includes effective tools for planning manufacturing and logistics processes. As their general feature, they can increase the efficiency of processes and process planning significantly. In addition, they may pay off in the first project. Their use is widespread in the automotive and electronics industry as well as in logistics service companies. Plant Simulation, is a system suitable for performing material flow simulation. In the classical sense, material flow is a description of the flow of a substance or product in plants [2] Tool Condition Monitoring is important procedure in the manufacturing processes. A number of researches focuses on tool wear estimation. Estimation of tool wear during CNC milling using neural network-based sensor fusion was executed by Ghosh et.al. Intelligent tool wear measurement of tool wear ratio in technological processes were carried out by Alique and Haber [23]. Estimation of flank wear with artificial neural networks in this experiment with back propagation neural network

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modelling is shown by Ozel and Nadgir in their research [26]. For tool condition monitoring multilevel perceptron was applied by Zuperl and Cus [27]. Rivero et al. [12] measured tool wear ratios by measurement techniques in case of high-speed milling process. Orhan et al. [24] estimated tool wear by vibration measurement method of AISI D3 cold steel in their experiments. Lister and Dimla [14] applied multi-layer perceptron neural networks. Tool condition monitoring using artificial intelligence methods has been made by Balazinski et al. [18]. Cho and Ko researched tool wear with fuzzy method and so-called inference algorithm in their research [25]. Wilkinson and Reuben [13, 22] used acoustic emission method for tool life estimation. This article focuses on applying the proper softwares and approaches with additional tool condition monitoring with vibration and acoustic analysis for manufacturing process optimization.

1. GraphIT

The software company graphIT Kft. appeared on the Hungarian CAD / CAM / PLM market in 1992, representing Siemens PLM, an international software development company, with the distribution of 3D design, processing design, finite element analysis and digital manufacturing solutions.

In addition, a Japanese production scheduling system (Asprova) was launched in 2014, for which an own-manufactured tracking system was developed, which ensures efficient coordination of production planning and manufacturing at several companies. After 2017, a Siemens-developed system was added to the range, extending the previous collaboration between the two companies. Preactor software assists companies to plan their weekly manufacturing tasks based on orders, resources, and other manufacturing parameters. [1] To meet increased customer expectations, graphIT Kft. has introduced an ISO 9001 quality management system, which covers both software distribution and professional support, as well as offering consulting opportunities for each CAD / CAM / PLM product they sell. [1]

2. Tecnomatix – digital manufacturing

Typically, 65% of the workforce of a company and 80% of its costs are related to manufacturing and production. As a result, manufacturing efficiency, or lack thereof, has a huge impact on costs. Manufacturing companies may even have a day-to-day problem of managing costs and revenue losses due to poor timing, optimization errors, large work-in-progress (WIP) rate, and inadequate resource utilization. Generally, companies focus on the costs that can be saved in terms of planning and material costs first, but to optimize the entire life cycle of a product, companies must deal with the optimization of processes that move manufacturing and production. The elements of Tecnomatix product family provide solution (Table 1). [2]

Plant Simulation	Plant Simulation	Plant Simulation	RobCAD, Process Simulate	Preactor

Table 1. Fields of digital manufacturing [2]

The most efficient way to improve manufacturing processes is to create a digital twin of real, physical production. Process development opportunities can be tested on the digital twin, as the behaviour of the digital twin is the same as its real production. Developments can be transferred from the digital twin to

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physical production. The most common tools for creating a digital twin (Figure 1) include Plant Simulation and Preactor. [2]

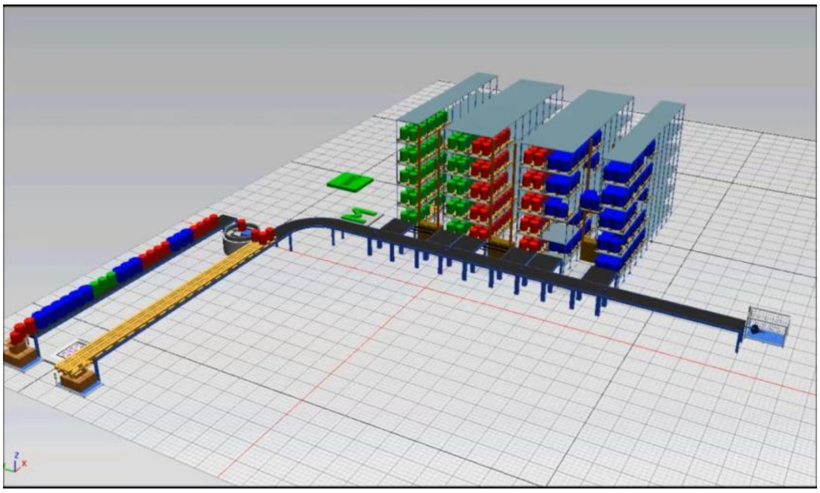

Figure 1. Digital twin created in Plant Simulation [3]

3. Plant Simulations

The software Plant Simulation in the Tecnomatix product range is an event-driven simulation tool that allows the creation of digital models of logistics systems (e.g., production lines) to learn about the characteristics of the systems and optimize their operation. [4] The digital models created in the program allow to perform various experiments or 'what if…' type tests without interrupting the process in the physical, real system. It can also be applied in the design phase so that the future operation of the actual production system can be tested before putting it into operation. [34]

Extensive analytical tools are available in Plant Simulation, such as bottleneck analysis, several statistical tools and diagrams that allow the evaluation of different principles, production process alternatives. [4] These tools can provide reliable results and information in the early stages of manufacturing planning, as they make it easy to model and simulate production systems and their processes, therefore, they can provide objective help before making an important decision. [34]

In addition, material flow, resource utilization, and logistics can be optimized at each level of plant design, from global supply chains to local factories to specialized production lines. [4] [34]

Main features of software [4]:

- Object-oriented models
- Open architecture (connectivity with multiple standard interfaces)
- Optimization process based on genetic algorithms
- Automatic analysis of simulation results
- HTML reporting tool

Benefits [4]:

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- Return in a relatively short time
- 15-20% increase in productivity
- 5-20% reduction in costs
- Optimization of resource use and reusability of data
- Inventory can be reduced by 20-60%
- Lead time can be reduced by 20-60%

Plant Simulation facilitates the preparation of process simulation tasks with user interface in Hungarian.

3.1. Factory, production line, process simulation and optimization

Plant Simulation, as mentioned before, is a system suitable for performing material flow simulation. In the classical sense, material flow is a description of the flow of a substance or product in plants (e.g., on a conveyor belt or even a vehicle). [5-8] [34]

Its most popular areas of application are the simulation and analysis of flow processes in the field of production cells, production lines and plant halls. In general, significant questions to be considered before simulation [5-8] [34] are as follows:

- How many workers, machines, storage cells, etc. are required?
- In a logistical manner: who? what? when?
- In terms of layout, where is the optimal place for machines and workers?

As Plant Simulation is a discrete, event-driven simulation system, it examines only discrete moments of relevant events that progress continuously. Such an important event may be, for example, when an item arrives at or leaves a conveyor element. Simulations of the manufacturing process can also be applied to detect low or excessive inventories, as well as under- or overloaded conveyors, and system bottlenecks that can result in a decline in production efficiency. [5-8] [34]

The Plant Simulation system provides numerous ready-made basic elements for both 2D and 3D simulation, but of course you can also create own elements. (Figure 2 and 3) [6-8]

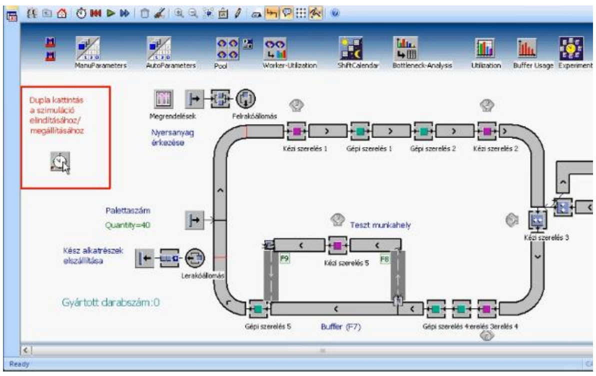

Figure 2. 2D interface and simulation interface [6]

Figure 3. 3D simulation image [7]

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The software can help the user identify and avoid problems that would require expensive and time-consuming repairs later during manufacturing, as well as minimizes the cost of a new production line without reducing productivity and optimizing the performance of existing systems (Figure 4) with parameters which results in the simulation can be checked well before the actual preparation. [5-8] [34]

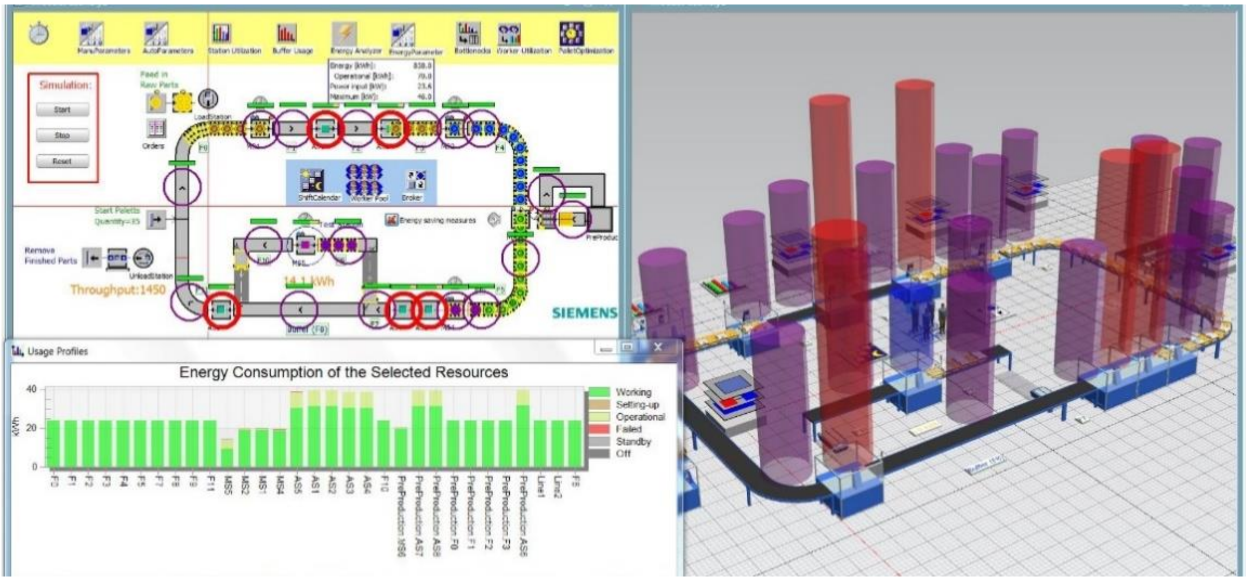

Figure 4. Performance optimization window [8]

In addition to key features, other features should be mentioned, such as object libraries, which help to perform the most typical modelling tasks quickly and efficiently, graphs and charts, which are applied to analyse output, resources, and bottlenecks (Figure 5.) provide comprehensive analysis tools, Sankey-diagrams and Gantt-graphs, integrated experience management, the genetic algorithm needed to optimize system parameters, and last but not least, open architecture and integration options (ActiveX, CAD, Oracle, SQL, ODBC, XML, etc.). [5-8]

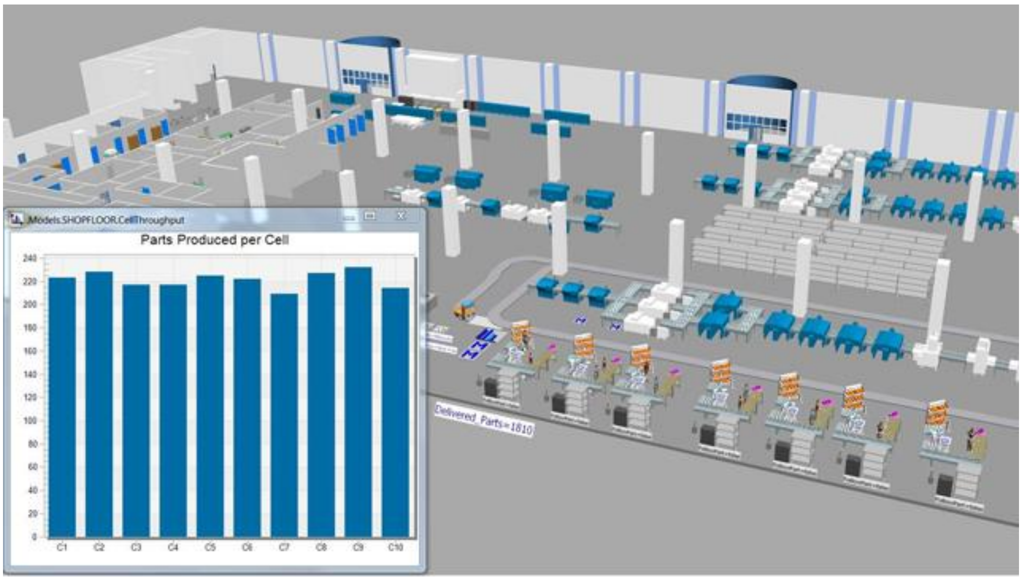

Figure 5. Bottleneck analysis [8]

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3.2. Value Stream Map (VSM)

Of the 5 basic steps in building a Lean system, the second is to map the process of value creation. The result of the activity is the so-called value stream map, i.e., its version; the current state map. Before starting the development of the process, it is expedient to summarize our goals in a so-called future state map. [9] [34]

Core functions of Plant Simulation value stream analysis

The Plant Simulation value stream analysis module goes beyond a value stream map on paper and enables to create a dynamic value stream map that has the following advantages over a paper-based tool [10] [34]:

- allows to manage several types
- the effects of process changes can be analysed immediately
- inventory (WIP) and warehouse levels
- on-going reserves can be examined
- determination of Kanban card number and Kanban sizes
- you can see immediately how much the value-adding part of the process is
- analysis can be performed directly on orders (as in a production schedule)
- the dimensions of the intermediate transport units are available

3.3. SmartTalk library

The SmartTalk library is a development of graphIT Kft., which implements light, visual programming in the Plant Simulation environment. (Figure 6) SmartTalk avoids the need for external programming assistance when creating Plant Simulation models, thus accelerating implementation, and reducing costs. In addition, simulation knowledge remains at the company in an easy-to-use and reusable form. [5-8] [11]

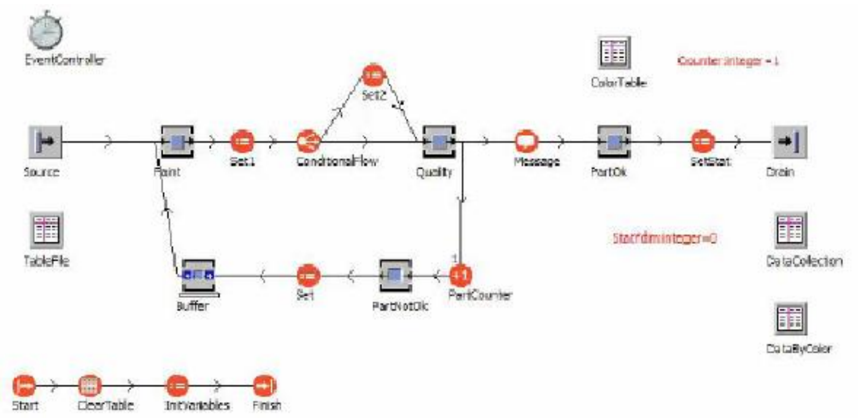

Figure 6. SmartTalk virtual programming [11]

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4. Tool wear types

Tool wear is generated by the contact forces, chemical reactions, and abrasive interactions. There are some critical types of wears. Flank wear where the tool in contact with the workpiece wear and it can be described by the Tool Life Expectancy equation.

According to studies, 50% of tool wear is caused by abrasion, 20% by adhesion, 10% by chemical reactions and the remaining 20% by the other mechanisms [17].

Tool wear is reduced with lubricants and coolants while machining which reduce friction and temperature, in this way tool wear can be lowered.

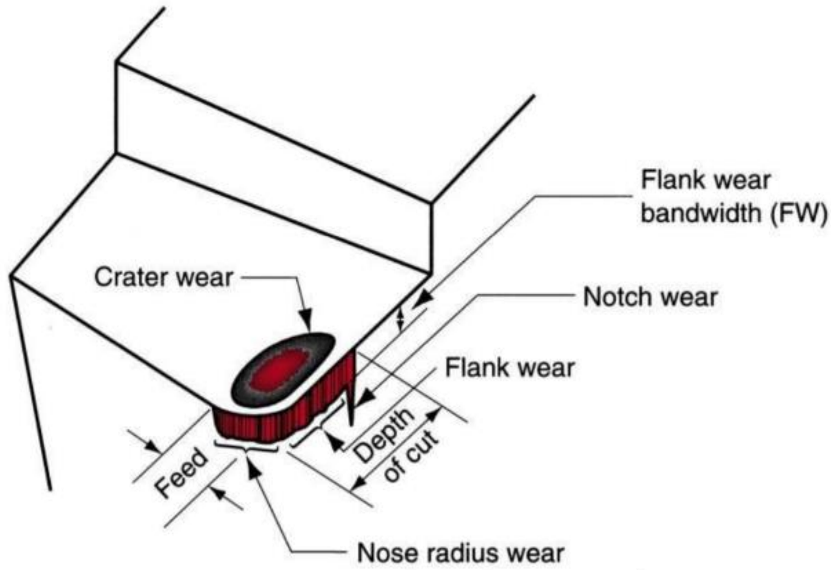

Figure 7 Cutting tool wear modes [33]

4.1. Tool wear estimation equation

For the calculation of tool life and estimating its RUL time:

$$V_C * T n = C \quad (1)$$

where Vc: cutting speed [m/min], C: tool life [min], T: cutting time [min]

For more accurate calculation, the following formula is applied:

$$T=C * V^{A} * f^{B} * ap^{D} * VB^{E} \quad (2)$$

where parameters in the equation as C: tool life [min], Vc: cutting speed [m/min], T: cutting time [min], ap: depth of cut [mm], VB flank wear [mm], f: feed [mm/rev], A, B, C, D, E: parameters of Taylor equation. The change of the VB is usually described by the function of cutting time and following linear and exponential curve in its last period (Figure 8.).

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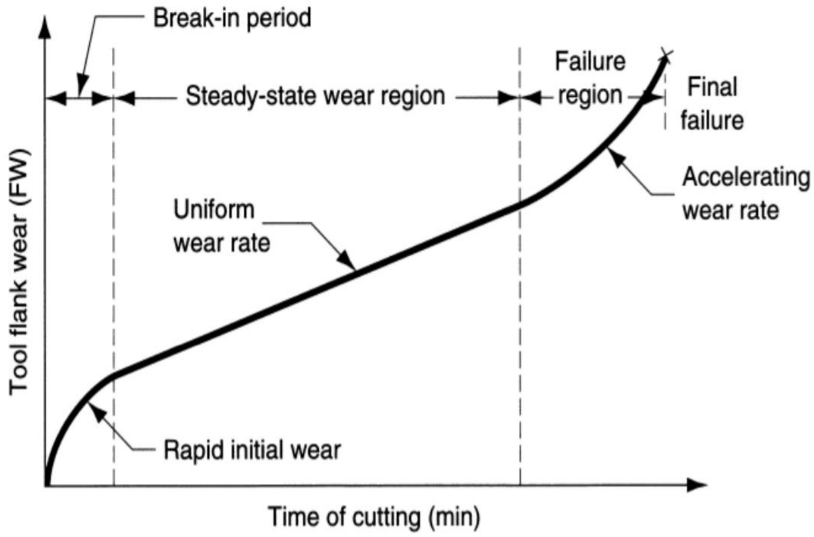

Figure 8 Tool remaining useful lifetime (RUL) curves [42]

4.2. Estimation of the tool wear rate by vibration and acoustic measurement

According to researches, cutting process vibration and its frequency are linked to the tool wear.

Jiang and Xu [28] executed researches and found the frequency occurs 0-117 Hz and in the range of 520 Hz.

Rao [6] found the next tool wear frequencies: 1850, 3200, 4800 Hz.

Due to the research of Akihito and Fujita [20], these frequencies are between 500 and 800 Hz and not higher frequencies.

Pandit and Kashou [19] conducted their researches on condition monitoring and they concluded that frequencies between 4300 and 4700 Hz are crucial for monitoring.

Weller et al. [16] found the large part of the tool vibration frequencies occur under 4000 Hz in the technological process that are used for tool wear measurement.

Martin et al. [21] measured the frequency range from 2000-2500 Hz and they found this interval is significant for determining the rate of tool wear by the vibration.

Fag et al. [15] determined two main parts; the first is under 150 Hz and the second is between 2000-2500 Hz. According to their findings, both ranges contain useful information for tool wear.

T. Mohanraj et al. [35] made effort to monitor the flank wear using wavelet analysis by extracting the Hoelder's exponent as a feature and using various machine learning algorithms to forecast the tool condition. The wavelet coefficients, Hoelder's exponent, and statistical features were extracted from the vibration signals. These features were used in such machine learning algorithms as SVM, KNN, Kernel Bayes, Multilayer perceptron, and Decision trees to forecast the flank wear.

T. Mohanraj et al. [36] applied online tool condition monitoring system which is highly essential in modern manufacturing industries for the rising requirements of cost reduction and quality

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improvement. The paper summaries various monitoring methods for tool condition monitoring in the milling process that have been practiced and described.

S. Shankar et al. [37] used an efficient tool condition monitoring system which was designed for keyway milling of 7075-T6 hybrid aluminium alloy composite with resultant machining force and sound acquired while the milling process. During the milling process, sound pressure and machining force were measured using a microphone and milling tool dynamometer with NI USB 6221 DAQ card and monitored using LabVIEW.

5. Experiment

5.1. Machine, technological parameters and measurement devices

As for tool for drilling, generally it is made of HSS, HSSE-Co 5 (5% cobalt content), HSSE-Co 8 (8% cobalt content) or solid carbide with 130° or 135° for hard and 118° for soft workpieces. The spiral angle is approximately between 20-40°. The spiral is stretched at a small spiral angle. It is important to use coating to extend the tool life, reduce the cutting time and temperature through friction mitigation. Titanium nitride (TiN) can provide much longer cutting time for the tool.

As the circumstances of the experiment, the following setup is used with the proper software for data analysis. Figure 9 shows a certain detail of the setup, there is list of tools and measuring devices below which are used for the experiment to extract data for condition monitoring. Microphone is placed 1.0 m away from the cutting area.

Figure 9 Boring machine with PCI IMI 603 C sensor for feature extraction for DSP

- Machine: Metabo BE 850-2 boring machine
- Tool: HSS-TiN, Diameters: 6, 8, 10, 12 mm, angle: 135°
- Workpiece: C45, 16MnCr5, 100Cr6
- Length of cut: 10 mm / Rev. Speed= 300, 600, 900, 1200 1/min, Cutting speed: 300, 600, 900, 1200 rev/min / Axial force: 25, 75, 150 N
- Microscope for VB measurement: Media-tech MT 4096 50-500 x
- Vibration sensor: PCB 603 C01, S-15PA

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- Microphone: PCB 130E20 electric
- DAQ units: NI 9234 DAQ, NI 9222 DAQ (for ultrasonic frequency analysis)
- Tachometer: Extech 461920
- Software: MATLAB, Labview

Figure 10 NI 9222 DAQ, NI 9234 DAQ, S-15PA transducer, PCB130E20 microphone, Extech 461920 tachometer

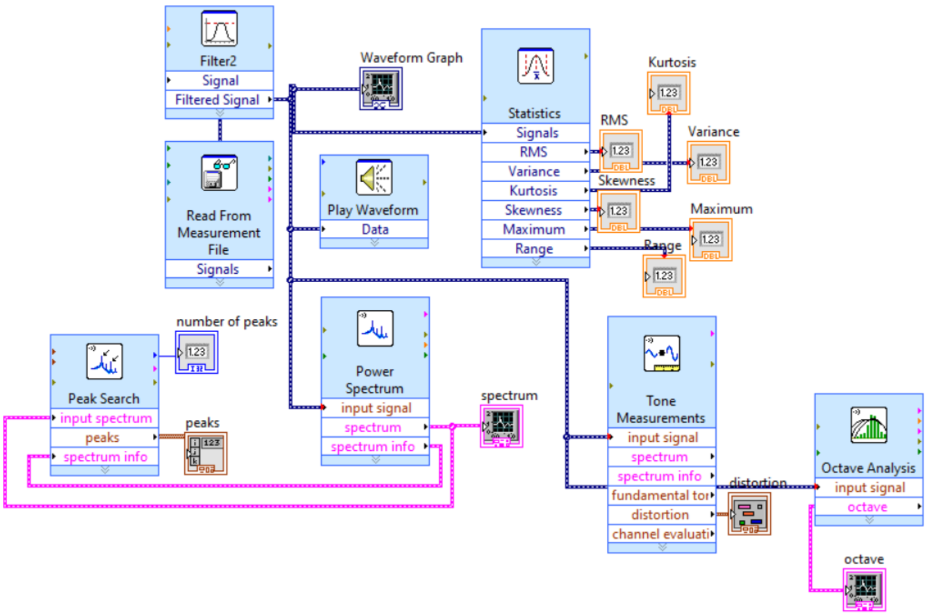

Figure 11 Labview VI for the vibration and acoustic measurement

5.2. Vibration and audio measurement results

Machining technological process generates vibration. Between the tool and workpiece cutting force, a signal is induced that can be analysed both in time-domain and frequency domain. In the experiment, vibration signal was picked in ultrasonic range up to 40 kHz. It was measured on healthy and worn tools after a cutting time of 2 to 30 minutes.

RMS	Variance	Kurtosis	Skewness	Maximum	Range
0.00028	0.9541	9.2534	-14.5895	0.04897	0.09758

Table 2. Time domain values of TiN worn tool after 30 mins cutting-time

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In Figures 12 and 13, vibration spectrum after a cutting of 30 minutes are shown in the audible and ultrasonic frequency range.

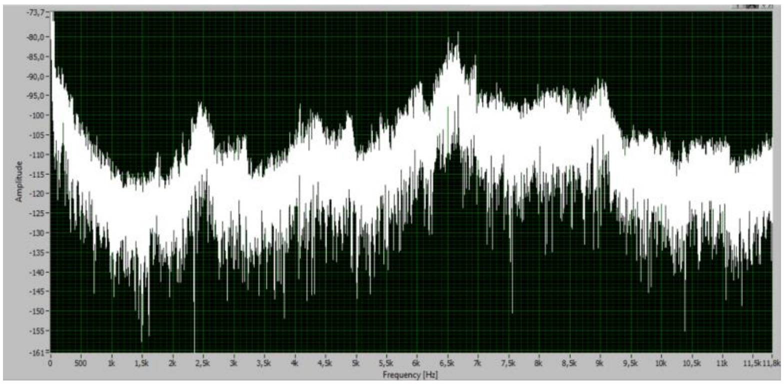

Figure 12 Representation of the frequency spectrum of TiN worn tool

In the range from 2.4 to 2.6 kHz and from 6.3 to 6.8 kHz there are peaks in the spectrum caused by excessive vibration. The energy content of these peaks increased from a cutting time of 2 mins up to 30 minutes but the spectrum remained nearly similar. Increase in energy content was occurred roughly 8 % as time spent from 2 mins to 30 mins. It was not significant but measurable difference.

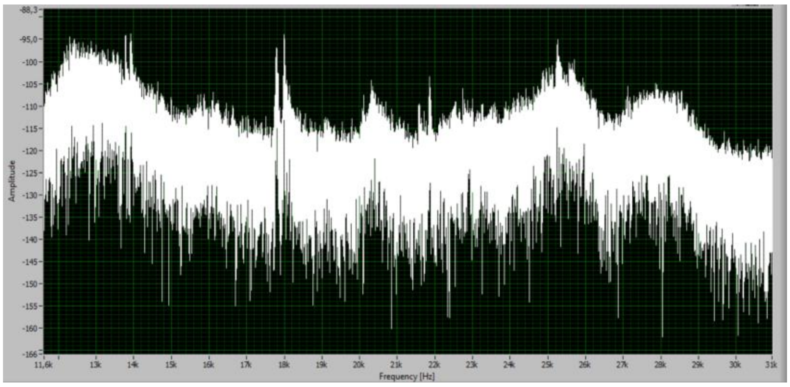

Figure 13 Representation of ultrasonic frequency spectrum of TiN worn tool

In the ultrasonic frequency range, there were peaks at 17.51 kHz and 17.95 kHz and increased energy content around 25.3 kHz. However, peaks of 17.51 kHz and 17.95 kHz showed higher values as cutting time and tool wear increased. Frequency did not change significantly as tool wear increased but the changes in the magnitude of the peaks were measurable to announce that they could be indicators for the tool wear.

Figure 14 shows the acoustic spectrum of the worn tool. It can be seen that there is significant audio energy of the spectrum between 50-60 Hz, 2.5 kHz and 6.5 KHz by octave analysis. The first result is insignificant, but 2.5 kHz and 6.5 kHz are similar to the measured values in the vibration analysis which means correlation between the vibration and the acoustic measurements. These frequencies remained nearly the same but showed higher values as tool wear increased.

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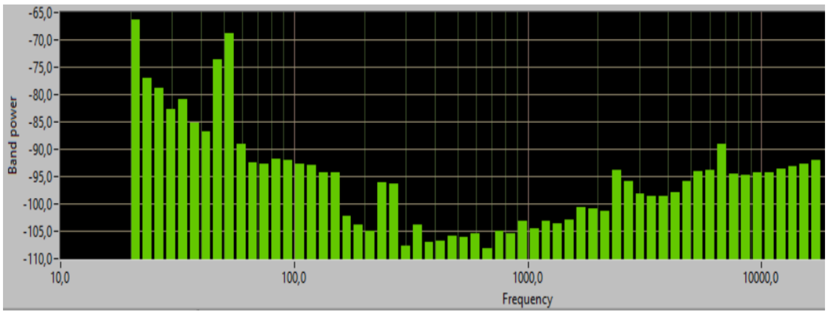

Figure 14 Octave analysis of TiN worn tool representation

Figures 15. and 16. represent the visible wear of the cutting tools under optical microscope which was the measurement method of the VB tool wear in the experiment.

Figure 15 Wear analysis with optical microscope under 100x magnification

healthy TiN tool (left), worn TiN tool of VB=0.3 mm (right)

Figure 16 Wear analysis with optical microscope under 100x magnification

Worn TiN tool of VB=0.1 mm (left), worn TiN tool of VB=0.3 mm under 300x magnification with chipped parts on the edge (right)

5.3. Tool wear estimation and optimization of cutting parameters

Cutting speed from 5 to 40 [m/min], feed = 0.1, 0.2, 0.3, 0.4 and 0.5 [mm/rev] and depth of cut of 0.1; 0.3 and 0.5 [mm] for C45, 16MnCr5, 100Cr6 materials with TiN tool with the extended Taylor equation. Table 3 shows the necessary cutting times to reach the actual 0.1, 0.2 and 0.3 tool wear due to calcualtion. In Table 4, the measured and the calculated wears are compared and there are slight difference between the values.

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Tool wear is featured by Taylor equation, as follows:

$$T=1.64 * 10^6 * V^{-1.87} * f^{-0.62} * ap^{-0.25} * VB^{2.64} \tag{3}$$

$$VB=1.85 * 10^{-3} * V^{0.64} * f^{0.47} * ap^{0.13} * T^{0.57} \tag{4}$$

n [rev/min]	300	600	900	1200	Tool wear [mm]
T [min]	43.28	32.17	24.75	17.87	0.1
T [min]	62.33	48.89	38.42	29.84	0.2
T [min]	84.68	71.56	62.44	48.95	0.3

Table 3 Influence of cutting speed and speed on tool life regarding the wear (VB)

Cutting time [min]	Measured tool wear [mm]	Calculated tool wear [mm]	Vibration [m/s2]	Noise level (dBC)
2	0.081	0.1432	2.98	71.6
5	0.112	0.152	3.14	72.8
10	0.132	0.1652	4.71	73.1
15	0.154	0.174	5.18	74.8
20	0.173	0.1828	6.32	74.2
30	0.192	0.1916	6.98	76.3

Table 4 Measured and calculated VB values, noise and vibration levels, n=1200 [1/min], f=0.10 [mm], ap=1 [mm]

5.4. Classification of tool wear with artificial neural network

Artificial neural networks (ANNs) are similar to the biological neural network in human brain. It consists of the network of neurons which have their own topology. Feedforwards and backpropagation (BP) networks are widely applied for both optimization and classification tasks in modern engineering. Neurons have their own weights and activation function has a significant role in the network. In the experiments, MATLAB application is used to create the proper neural network to tool fault classification where algorithm is modified for better classification.

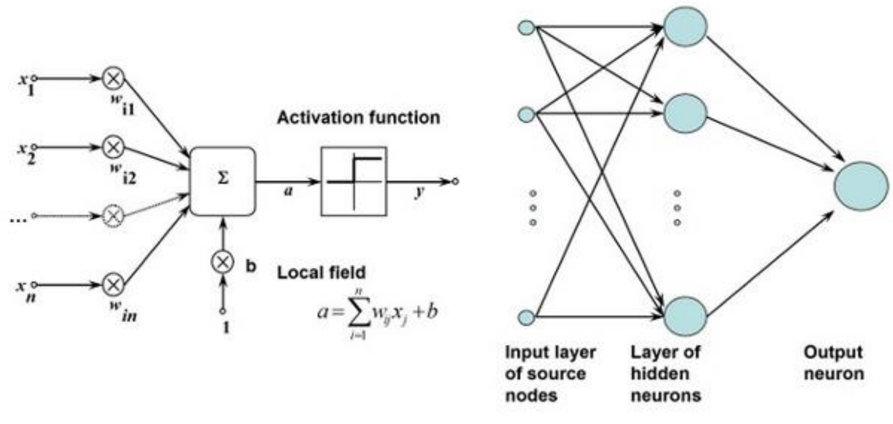

Figure 17 Principle of ANN structure and its topology in the experiment [30]

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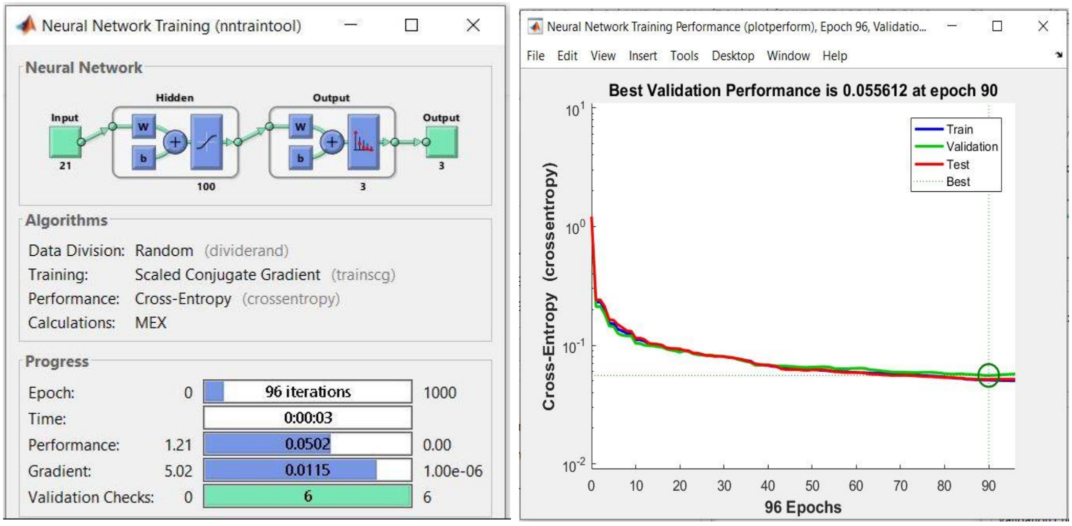

Figure 18 Training and classification of tool wear with scaled conjugate algorithm with ANN

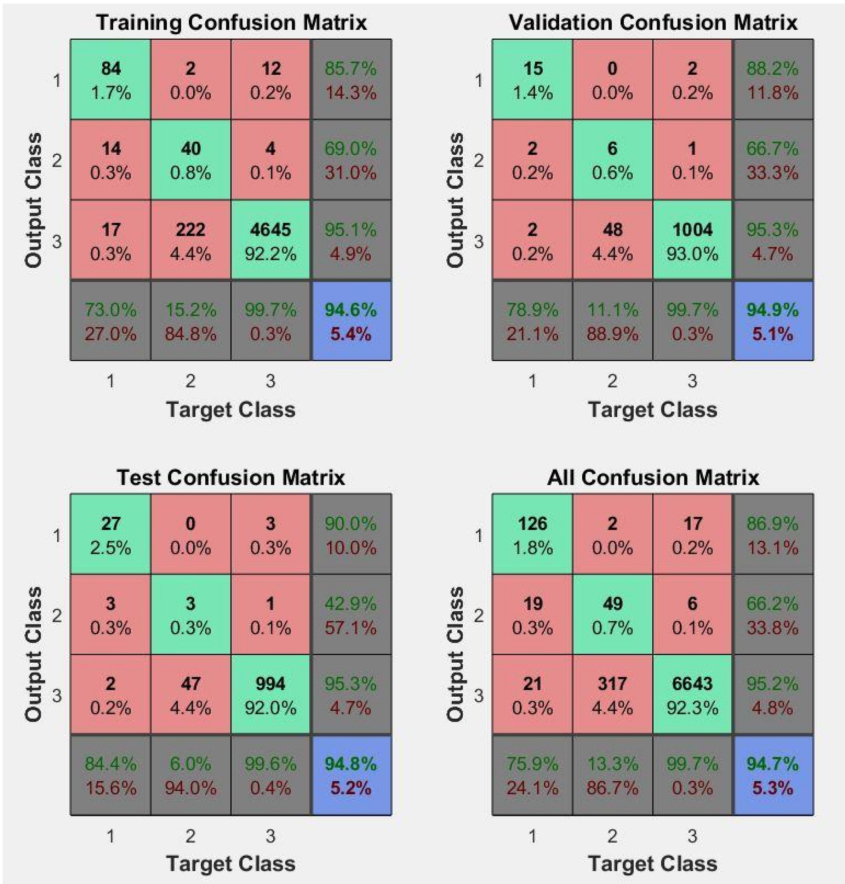

Figure 19 Training and classification of tool wear with scaled conjugate algorithm with ANN

For the tool wear classification training, testing and validation data were separated. 75% were chosen for training and 10% -10 % for the testing and validation. Two algorithm were used, scaled conjugate gradient and Levenberg Marquardt. They provided nearly the same result but of course the methods are stochastic. 94.7% of the data were classified as faulty. Figure 17. shows the ANN network and the iterations and Figure 19. shows the confusion matrices from MATLAB. Figure 20. Represents the ROC analysis of the investigation.

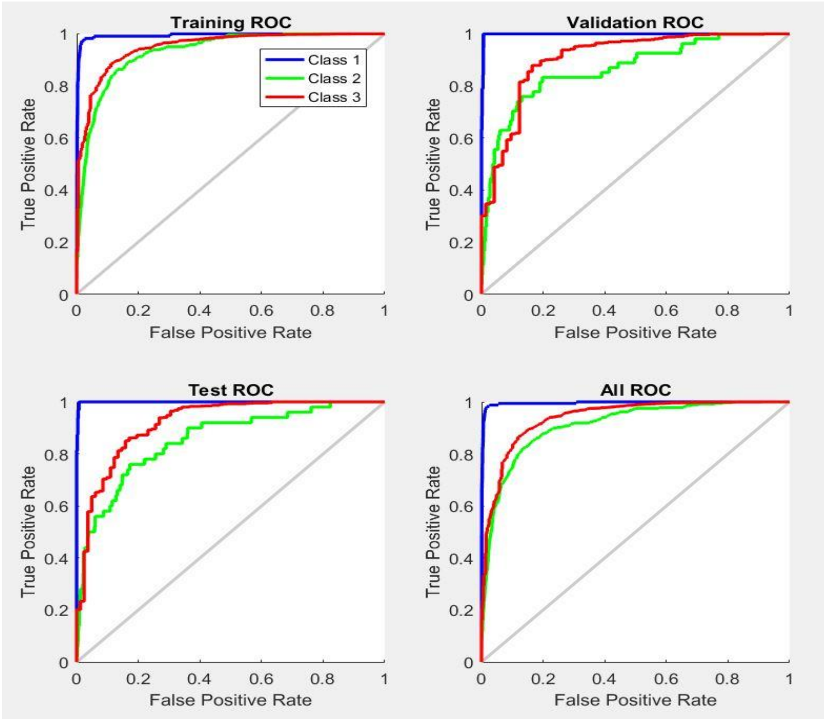

Figure 20 Receiver operating characteristic (ROC) analysis of tool wear with scaled conjugate algorithm with ANN

6. Conclusion

This article provides a comprehensive overview of the structure and use of the Tecnomatix production simulation and optimization program. With the software, we have the chance to optimize and correct problems in production and manufacturing. The use of the software is essential for any plants equipped with modern Industry 4.0 tools, in addition, lean principles are applied while using the program. Training in software simulations is essential in university education and industrial settings.

Tool condition monitoring was presented in the paper with experiments in technological boring process. Edge wear was monitored by vibration diagnostics, acoustic method, and optical way by microscope. The calculated tool wears by the extended Taylor equation were compared to the measured values by optical microscope. Generally, the difference between these values were under the acceptance limit for engineering applications. Therefore, method based on vibration measurement considered to be right method for tool wear and remaining useful lifetime (RUL) estimations. An additional acoustic octave analysis method was applied to reveal the possibility for using tool wear condition. There were correlation between vibration and acoustic method, but vibration diagnostics seemed to be more advantageous for tool condition monitoring. Considering the accuracy, CPU time, iterations neural network with scaled conjugate algorithm seemed to be the most efficient. ANN with scaled conjugate and Levenberg Marquardt algorithms were proper for tool fault classification as well, confusion matrices provided as high as 94.7% reliability considering the all data.

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