Automatic identification of drill condition during drilling process in standard laminated chipboard with the use of long short-term memory (LSTM)

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***Abstract*—This paper presents a new approach to the identification of the state of drill wear and tear during the drilling process. Identification provides for three states (classes) of drill which were marked according to traffic lights classification: red – "useless" (worn out), yellow (still sharp but should be manually assessed by a specialist), green -"useful" (sharp). Red state indicates symptoms of drill worn out and determines that it should not be used during the drilling process (does not satisfy the furniture process quality). Yellow drill state should draw attention to the fact that the drill may be excessively blunt. Later on, it is recommended to assess the drill manually. When the system indicates the green state of drill, it means that the drill may still be used in the drilling process, maintaining the high quality of drill holes. The recognition of drill state is based on 5 registered signals: feed force, cutting torque, noise, vibration and acoustic emission. The hardest part in the implementation of automatic identification of drill condition is to find appropriate features, which will separate cases belonging to 3 classes (states). When input data are presented in the form of images, we can use the convolution neural network, but in that case we have signals registered as time series, hence the long-short term memory (LSTM) is applied.**

Keywords—deep learning; long short-term memory; tool condition monitoring, drill condition.

I. INTRODUCTION

Industry development, requirements concerning competitiveness and necessity to maintain their high quality require that manufacturers maximize the automation of technological processes. It does not differ in the wood industry. Therefore, the aim of this paper is to develop the foundations of an automatic intermediary system (non-invasive) identification of the state of drill wear and tear, based on selected measurement signals, such as feed force, cutting torque, acoustic emission, noise and vibration. The development of such a system will allow, in the long term perspective, to eliminate the operator from the cutting tool who monitors the process and the machining process. It also allows automatic exchange of worn tools, which will increase the efficiency and consequently will reduce the number of stops, decrease production costs and improve quality.

The problem of automatic cutting supervision, based on indirect (non-invasive) identification of this condition, is for many years dealt with by many scientific centers around the world. The basic component of such a supervisory system is the diagnostic tool system [1,2].

When determining the blade wear, two diagnostic methods can be used: direct and indirect.

Direct methods are associated with the identification of changes in the tool geometry. They are accurate and consist of measurement of a specific blade wear and tear indicator [3]. Their basic disadvantage is the measurement, which must be performed by the operator and requires stopping the machining process.

Indirect methods consist of measuring changes in physical quantities, originating from the cutting zone by means of suitable sensors [4-12]. These methods are less accurate because they depend on many factors, including: selection of signals and appropriate measures of these signals related to blade wear and tear, measurement accuracy, external factors, such as interference with signal recording (e.g. noise) and different ways of fixing the sensors. Their main advantage is the fact that they enable continuous operation of machines eliminating unnecessary stoppage of the machine tool, and hence shortening the machine downtime and increasing the efficiency of the technological process.

Therefore, there is a great need to develop and implement methods of non-invasive diagnostics, which will eliminate the necessity to perform direct measurements of the degree of wear and tear of the cutting tool blade.

In this paper, we discuss the issue concerning the creation of novel indirect. We chose the method which allowed us to eliminate serious issues of the following approaches: features generation and then features selection processes. We chose one of the algorithms belonging to a wide learning group, which can teach us how to recognize drill conditions without providing diagnostic features. This is a novel method long short-term memory algorithm (LSTM), which uses time series (sequences) to recognize different classes. LSTM will assign the current drill state to one of three classes. These classes are contractually defined as: "green", "yellow" and "red" (by analogy to traffic rules).

II. MEASUREMENT METHODOLOGY

Data acquisition was performed using a standard Busellato Jet 100 CNC vertical machining centre, which is presented below. For experimental purposes, we used laminated chipboard and drills with a 12 mm diameter, with tungsten carbide tips (Figure 1 and 2).

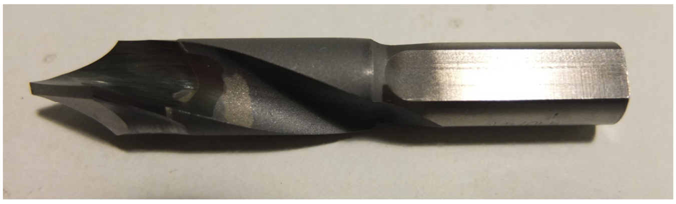

Fig. 1. Drill used in experiments

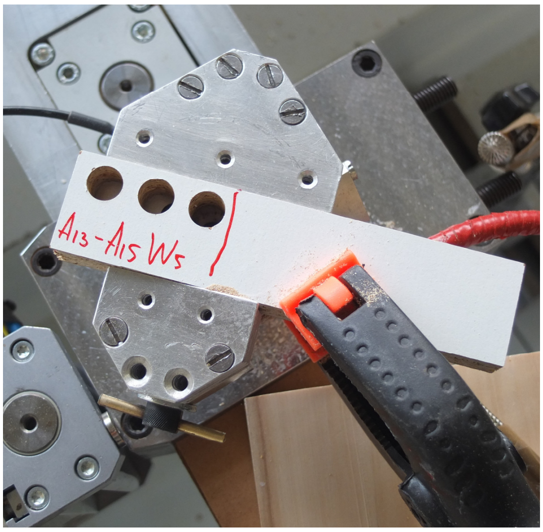

Fig. 2. Standard laminated chipboard used in experiments

During the acquisition process, the following physical features were collected:

- feed force (denoted as F),
- cutting torque (denoted as M),
- noise (denoted as C),
- vibration (denoted as V),
- acoustic emission (denoted as AE),

All the aforementioned types of signals were registered using the following special sensors:

- AE-acoustic emission measuring system (Kistler 8152B contact sensor, Kistler 5125B amplifier),
- V-mechanical vibration measuring system (Kistler 8141A accelerometer, Kistler 5127B amplifier),
- C-noise (sound pressure) measuring system (B&K 4189 microphone and preamplifier, B&K NEXUS 2690 amplifier),
- F and M – dynamometer with Kistler 9345A sensor and ICAM5073A amplifier.

The registration of selected signals was performed on the computer in the National Instruments Lab ViewTM environment, using NI PCI-6034E and NI PCI 6111 data memory cards. The use of two cards was justified by the presence of signals with different frequencies. The AE registration required the use of a relatively high sampling rate of 2 MHz, and other signals were recorded at 50 kHz. The cards reached signals through BNC - 2110 connection boxes, separately for each frequency range.

Of the six drills used for the experiment, five were subjected to blunting cycles, and one served as a control. The control drill was used only to record signal measurements, in order to compare the signal waveform. Registered signals of the reference drill (sharp enough) were also used to create a teaching set of a non-invasive system, identifying the state of the tool.

While monitoring the degree of wear and tear of the blades, the external corners of drills were collected with a digital microscope camera (Figure 4). The data obtained during microscopic measurements allowed to determine that the standard W index (the size of the external corner of the drill) may be useful in practice as a direct indicator of the wear and tear status of the drills when processing laminated particle boards.

Fig. 3. Determining the size of the wear indicator of the external corner (W) of the drill

The state of tool wear and tear is assessed on the basis of W index. However, it was recognized that for practical purposes there is no need to estimate the current value of W, because the most important is to distinguish three different states of the tool, which are referred to as “green”, “yellow” and “red”.

III. DATABASE

The basis for the determination of states (red, yellow, green) are the appropriate ranges of W values. The upper limit of the green state is generally accepted in the operation of tools and from the literature data and recommendations of tool manufacturers it follows that tool classes up to 0.2 mm are perfectly acceptable. The lower limit of the red state was adopted on the basis of literature data [13]. Yellow state is set between them. The classification concerning drill wear and tear is presented in Table 1. Each class is assigned a label on the basis of which the classification is made, i.e. the division of input data.

TABLE I. CLASSIFICATION BY WEAR AND TEAR CLASS

Wear ranges (W) [mm]	Class name
<0.2	Green
<0.2-0.35>	Yellow
>0.35	Red

During the data acquisition, special sensors collected totally 242 time series of 5 different physical quantities. Data distribution is presented in Table 2.

TABLE II. DATA SETS ACQUIRED IN EXPERIMENTS

Number of drill	Number of trials for green class	Number of trials for yellow class	Number of trials for red class	Total number of trials
0	27	0	0	27
1	15	10	20	45
2	20	10	15	45
3	15	10	10	35
4	10	15	20	45
5	15	15	15	45
Drill No. 0- reference drill			Total:	242

In Table 3, the summary of training and testing sets is presented. It was assumed that the system is taught on 4 drills plus the control drill, which is the training set. The test set constitutes the fifth drill. The result is 5 sets, because each drill has a test function in turn.

TABLE III. STATEMENT OF TRAINING AND TESTING SETS

Number of test	Training set	Test set
1	197	45
2	197	45
3	207	35
4	197	45
5	197	45
Reference drill – always training set		

IV. LONG SHORT TIME MEMORY ALGORITHM

To avoid spending time on generation and then selection of processes of diagnostic features to classify drill state to one of 3 classes (green, yellow, red), we were looking for a new algorithm, which will not require handcrafted diagnostic features provided to classifier. One of the most efficient and popular group of algorithms is deep learning. Deep learning, or the so-called deep structured learning or deep machine learning, is currently a very popular classification approach, especially efficient in case of images [14-18]. But in this approach we do not have images as input, so we had to find an algorithm, which can provide time series data as input.

One of the novel approach in deep learning algorithms group for times series purposes is long short-term memory (LSTM). This network is much faster than the previous recurrent network algorithms, such as RTRL, BPTT, Recurrent Cascade-Correlation, Elman nets, Neural Sequence Chunking and solves complex and artificial long time tasks [19]. In case of Back-Propagation Through Time (BPTT), we can have oscillating weights, while Real-Time Recurrent Learning (RTRL) takes a lot of time. Sometimes it does not work at all [19]. The solution to overcome error back-flow issues is the LSTM approach. LSTM is able to learn how to bridge time intervals in excess of 1000 steps, even when we have too much noise in signal or incompressible input sequences and, most importantly, does not lose short-time lag capabilities [19]. It is caused by an efficient gradient-based algorithm, which dynamically changes the “constant” error flow through internal states of special units. For example, gradient computation is cut at certain architecture-specific points without impact on long-term error flow [19].

LSTM network in the form of classification approach usually consists of 5 layers: sequence input layer, LSTM layer, fully connected layer, softmax layer and classification layer [20]. Of course, if we want to have a more deep network, we can add more sequence LSTM layers, but learning time will be much slower than in the case of only one LSTM layer. Sequence input layer size must be the size of feature dimension of input signal, while the size of fully connected layer should constitute an equal number of classes for classification purposes (3 classes in this paper).

V. NUMERICAL EXPERIMENTS

Our database consists of 242 trials of 5 measured physical quantities, such as: feed force (F), cutting torque (M), noise (C), vibration (V) and acoustic emission (AE). For every signal, we applied 1024 trial window lengths. So, it means that we divided time series into 58 windows of 1024 length. For every window in time series we calculated 32 points DFT (Discrete Fourier transform). So, we have 5 (signals) x 32 points DFT, totally 160 features, as well as Spearman and Pearson correlation between signals. Thus, we finally obtained 242 trials with 180 features of 58 sequences.

During experiments we tested many architectures, but finally the following architectures provided the best results:

1. Sequence Input Sequence input with 180 dimensions
2. LSTM layer LSTM with 500 hidden units
3. LSTM layer LSTM with 200 hidden units
4. Fully Connected 3 fully connected layer (3 classes)
5. Softmax softmax
6. Classification Output crossentropyex

We collected 242 trials on the basis of 6 drills (one of them is the reference drill). According to wood technology specialists, we decided to teach LSTM using all trials belongs to 5 drills and testing on the last drill. It means that every drill will be intended for testing and none of its trials takes part in the training process.

VI. NUMERICAL EXPERIMENT RESULTS

We performed 6 tests in which every drill plays the role of the testing drill. According to wood technology specialists, the results at the level of 81% are satisfying from the point of view of the production process. Details of numerical experiment results are presented in Table 4.

TABLE IV. RESULTS OF APPLYING LSTM IN DRILL CONDITION CLASSIFICATION TO 3 CLASSES (GREEN, YELLOW, RED) ON THE BASIS OF 242 TRIALS .

Number of drill tested	**Training accuracy**	**Testing accuracy**
Drill 1	100%	100%
Drill 2	100%	88.89%
Drill 3	100%	77.78%
Drill 4	100%	65.71%
Drill 5	100%	88.89%
Drill 6	100%	66.67%
Average	100%	81.32%

VII. CONCLUSION

This paper presents the application of the long short-term memory (LSTM) network in the recognition of the state of the drill on the basis of the set of 5 registered different types of physical quantities.

The main advantage of such approach is the application of time series or any other sequences (DFT in this paper) to one of deep learning algorithms, without spending too much time on hand-crafted feature generation.

The presented results of numerical experiments confirmed good performance at the level of 81% in the recognition of three sharpness states of the drill and based on wood technology specialists, they can be applied in production processes.

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