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Pawel LEZANSKI[1*]

A DATA-DRIVEN PREDICTIVE MODEL OF THE GRINDING WHEEL WEAR USING THE NEURAL NETWORK APPROACH

Advanced manufacturing depends on the timely acquisition, distribution, and utilization of information from machines and processes. These activities can improve accuracy and reliability in predicting resource needs and allocation, maintenance scheduling, and remaining service life of equipment. Thus, to model the state of tool wear and next to predict its remaining useful life (RUL) significantly increases the sustainability of manufacturing processes. there are many approaches, methods and theories applied to predictive model building. the proposed paper investigates an artificial neural network (ANN) model to predict the wear propagation process of grinding wheel and to estimate the RUL of the wheel when the extrapolated data reaches a predefined final failure value. The model building framework is based on data collected during external cylindrical plunge grinding. Firstly, usefulness of selected features of the measured process variables to be symptoms of grinding wheel state is experimentally verified. Next, issues related to development of an effective MLP model and its use in prediction of the grinding wheel RUL is discussed.

1. INTRODUCTION

The idea of intelligent manufacturing systems has become a very stimulating subject in industrial production for the last twenty years. It requires manufacturing systems to be able to self-recognize the current state of all of their components and next to adapt their activities to the recognized conditions of production. The newest approach to this idea is the conception of the fourth industrial revolution named as Industry 4.0 [1,2]. This is a data driven production model in which all components of production systems in the form of cyber-physical systems (CPS) [3] communicate and interact with each other using an advanced network called Internet of Things (IoT) [2]. Implementation of such a conception requires present, local monitoring and production control systems to be replaced with the CPSs which link cyber space of Internet with material space of production [4]. Moreover, condition-based maintenance of the equipment and the performed processes has to be based on information about remaining useful life (RUL) of the system components. Accurate prediction of the equipment and tool RUL in such manufacturing systems is one of the crucial elements of effective implementation of the CPSs.

[1] Lodz University of Technology, Institute of Machine Tools and Production Engineering, Lodz, Poland
[*] E-mail: plezan@p.lodz.pl
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In the area of machining processes, among them also for grinding processes, the state of tool cutting ability has a basic meaning for final quality of the workpiece and economical results of given processes. However the wear propagation process of grinding wheels belongs to one of the most difficult in the domain of tool condition monitoring. Phenomena like irregular geometry and random changes of the number of active cutting edges on the wheel cutting surface (WCS), as well as self-sharpening of them are the source of this difficulty. The wear process of grinding wheels can arise in three different forms or in a combination of them:

- dulling of abrasive grains (attritious wear),
- cracking or pulling of the grains out (fracture wear),
- gumming up of the WCS with chips (wheel loading).

Usually a combination of all of the wear forms take place but during grinding with a properly selected set of parameters the attritious wear and fracture wear should dominate. The wheel loading is always rather the undesirable form of wheel wear and should be eliminated through the selection of the correct grinding wheel to the workpiece material.

The fracture wear creates newly exposed sharp edges of grains on the WCS what causes a self-sharpening process of the wheel but also its radial wear (changes in its external shape and volume decrease). The attritious wear contributes insignificantly to the shape and volume changes however directly influences the level of grinding forces and temperature thus in this way it also has an impact on the fracture wear [5].

The grinding wheel condition monitoring has been intensively investigated by many researchers. One of the first broad survey of these investigation is given in [6]. An important conclusion which results from this work is that there is a lack of a clear recommendation for the best set of features for grinding wheel monitoring. The most effective features depends on the process type and its conditions. They should be selected from number of features offered with some redundancy by measuring and data processing units used for the given process. Next, a feature integration method should be chosen for the wheel wear process modelling [7].

Many works on grinding wheel condition monitoring during surface grinding have been done by T. W. Liao [8-11]. He used different features of the acoustic emission (AE) signal in time and frequency domains as well as different statistical and artificial intelligence classification techniques for the wheel state estimation. Results of these studies proved that the quality of classification depends on a correct signal feature selection, the cardinality of the learning vector and the grinding conditions. The best results (even up to 100% of appropriate decisions) were obtained for higher values of the specific material removal rates using the discrete wavelet decomposition of the AE signal and different methods of cluster analysis based on a distance matrix generated with the aid of the hidden Markov model. The grinding wheel wear during curve grinding using a white corundum grinding wheel was investigated in [10,12]. The authors took advantage of the combinational information of the decomposed vibration signal frequency components based on the wavelet packet decomposition. They concluded that the extracted features can be used in qualification of wheel wear condition and applied in prediction of the wear. A complex monitoring and controlling system for cylindrical grinding process was proposed in [13,14]. An artificial neural network (ANN) was used for estimation of the wheel life in this system.

A hybrid system for grinding wheel condition monitoring during external cylindrical grinding was proposed by Lezanski [15]. The system utilized data and their different processing methods from AE, vibration and grinding force components signals. A feed forward ANN was used for signal feature selection procedure using the weight pruning method and a neuro-fuzzy system for wheel condition estimation. The ANN could also be used for wheel condition modelling and estimation. The Dominance-based Rough Set Approach (DRSA) is proposed as a methodology for plunge grinding process diagnosis including the state of grinding wheel catting ability in [16]. A set of decision rules modeling the WCS wear propagation considering changes in its waviness and topography was generated based on a feature set extracted from the 14 features of measured signals. The presented studies indicates that in spite of the difficulty of grinding wheel wear propagation modeling of this process is a crucial topic for grinding effectiveness. Thus to allow grinding processes to be a valuable part of CBSs in Industry 4.0 based manufacturing there is a need to develop studies on grinding wheel wear propagation into research on predictive model building.

Prognostic methods can be classified into four groups [17]:

- physics based methods,
- artificial intelligence based data driven methods,
- statistics based data driven methods,
- model based methods.

Because each of individual method possesses not only advantages but also drawbacks, to overcome this problem, different types of integration of these methods are also used to obtain better performance in a given application. A detail discussion on strengths and weaknesses of all of the prognostic methods with a comprehensive survey of their applications to prediction of RUL of cutting tools is presented in [17] (none of the discussed applications is related to abrasive tools).

The focus of this paper is to develop an artificial neural network (ANN) model to predict the wear propagation process of grinding wheel and to estimate the RUL of the wheel when the extrapolated data reaches a predefined final failure value. The model building framework is based on data collected during external cylindrical plunge grinding. Firstly, usefulness of selected features of the measured process variables to be symptoms of grinding wheel state is experimentally verified. Next, issues related to development of an effective ANN model for prediction of the grinding wheel RUL is discussed and presented.

2. THE PREDICTIVE NEURAL NETWORK

The structure of predictive neural model proposed in this research is based on the ANN model used by Tian at al. in 18]. However the applied training algorithm is different to obtain shorter times of the training procedure convergence and lower mean square errors.

The structure of the proposed ANN model is presented in Fig. 1. It is a two-layer-feedforward neural network. The first layer is the hidden layer with sigmoid neurons and the second layer is the output layer with linear neurons. Such a network with an appropriate number of neurons in the hidden layer using a consistent data set for training is able to map well input data into corresponding output data. Therefore, this type of networks frequently have application in development of models for estimation and prediction of different phenomena [19].

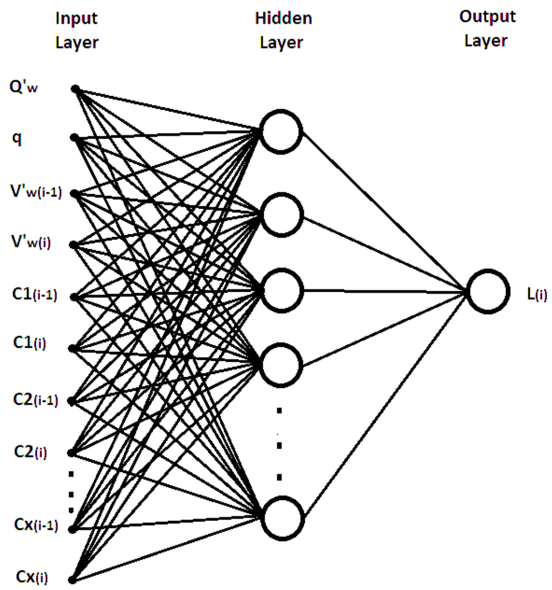

Fig. 1. The structure of predictive neural network model

The inputs to the network include the wheel life period values and the values of the features chosen as symptoms of the wheel condition. All these inputs are the measures identifying the wheel condition at the current inspection point and those at the previous inspection point. For example: if $C1_i$ is the value of the feature number *1* at the current inspection point *i*, $C1_{i-1}$ is the value of this feature at the previous inspection point *i-1*. The volume of material removed from the workpiece per a grinding width unit since the last wheel dressing operation V'_w [mm^3/mm] (the specific material removal) is used as the measure of the wheel life period. Thus, $V'_{w(i)}$ is the value of specific material volume at the inspection point i and $V'_{w(i-1)}$ is the value of this volume at the previous inspection *i-1*.

The two grinding parameters: the specific material removal rate Q'_w, and the speed ratio q applied in each single grinding sample were additionally used as inputs to the network to take into consideration their influence on the grinding wheel wear process.

The output of the network, denoted by $L_{(i)}$, is the value of the wheel life period achieved at the current inspection point *i* for a given grinding sample expressed as the percentage of the full life period achieved for this grinding sample. For example, if the full wheel life is equal to 429 [mm^3/mm] and, at an inspection point *i*, the life period is equal to 300 mm^3/mm, then the output value is equal to $L_{(i)}$ = 300/429 x 100% = 69,93%.

From among many algorithms available for training feedforward neural networks, the Levenberg-Marquardt (LM) algorithm was chosen for application to the proposed network training. This algorithm seems to be very suitable for the considered application because it is recommended for fitting problems and networks containing up to a few hundred weights. The LM algorithm requires more memory but is able to obtain lower mean square errors in shorter processing time than any of the other algorithms [19].

One of the basic problems related to the results of neural network training is called overfitting. It can happen when the network is trained to minimize the mean square error only with the use of training set of data. As a result, the obtained network over fits the training samples but it does not have capability for generalization of new examples. A method called early stopping is used to overcome this problem.

When the early stopping is used the available data is divided into three subsets: training, validation and testing. The first one is used for iterative calculating the mean square error after each epoch of training data and updating the network weights and biases. Simultaneously, the mean square error is monitored using the validation set. The validation error usually decreases during the initial phase of training, as does the training set error. However, when the network begins to over fit the training data, the error on the validation set typically begins to rise. This is the moment when the training should be stopped, and the weights and biases obtained at the minimum of the validation error should be returned as the optimal. The testing set error is used only to check how the obtain network fits the data earlier unknown to the network. If the error in the testing set reaches a minimum at a significantly different iteration number than the validation set error, this might indicate a poor division of the data set [19].

3. THE GRINDING PROCESS DATA BASE

3.1. DETERMINATION OF GRINDING WHEEL LIFE CRITERION

The external cylindrical plunge grinding process was chosen as the object of the presented research because it is one of the most commonly used types of grinding and it is characterized by a number of specific features resulting from its kinematic and geometric conditions. The workpiece, as well as the tool, performs rotary motions in this type of grinding and their peripheral surfaces possess an initial waviness and out-of-roundness errors. During grinding, as a result of these rotating motions, a phase shift arisen between the waves of the workpiece and the wheel causes a change of grinding depth after each revolution of them. In consequence, this process leads to continuous change of the waviness amplitudes on the workpiece and wheel and to a relative, self-excited vibration between them. This process is modulated by the phenomenon of wave geometrical interference which can result in the cut down of waves on the wheel and the workpiece, The degree of this cut down is expressed by a coefficient which is equal to the ratio between the height of the wave remaining correspondingly on the wheel and the workpiece surface and the amplitude of chatter generating this wave. The threshold frequency for a workpiece above which the cut down of the waves begins in conventional grinding is lower than 500 Hz, whereas this frequency for the wheel, because of a much higher grinding ratio, is at least 100 times higher. Chatter frequencies in cylindrical grinding, which are close to the natural frequency of the mechanical system [20], are usually higher than the workpiece chatter frequency, but much lower than the wheel chatter frequency. This means that wheel waviness can develop to a very high amplitude and explains why nearly all cylindrical grinding processes run under instability, taking into account the wheel regenerative chatter.

An excessive development of the WCS waviness can lead to very dangerous events thus its amplitude value has a superior meaning to all of the others wheel life criteria. This is why the value of the WCS waviness amplitude is used as a grinding wheel life criterion in the presented research.

3.2. DATA COLLECTION

Grinding monitoring data were collected during tests carried out on a modified cylindrical grinding machine equipped with adequate control and measurement units [16,21]. During the tests the workpieces made of 38HMJ steel hardened to 53 HRC were ground using the 38A80KVBE grinding wheel. The range of grinding parameters applied during the tests exceeded the acceptable working ranges so that the diagnosis of phenomena like the wheel life period would be possible. To achieve this purpose, a specific material removal rate equal to 1, 2 and 3 mm^3/mms, a speed ratio equal to 60, 100 and 400 and the wheel speed equal to 40 m/s were used. The tests were carried out in series. Each series represents a sequence of grinding cycles completed to the point at which the state of the grinding process was recognized as unmanageable because of appearance of such phenomena like huge vibrations or workpiece surface burn. For this reason, depending on the applied parameter combination, the individual series consist of 8 to 12 grinding cycles that were 400 to 600 mm^3/mm of the specific material removal and for each series this was a higher volume than the recommended grinding wheel life.

The force grinding components, vibration and the RMS value of the acoustic emission signals were recorded during each grinding cycle, whereas the raw AE signal was recorded every second grinding cycle. The vibration signal was measured by the 4370 B&K piezoelectric transducer mounted on the tailstock centre casing. The 3000R Gap Dittel wireless AE was applied for the measurement of the raw and, after an analogue RMS circuit processing, the RMS value of the AE signal. This sensor was attached to the face of the grinding wheel spindle [16,21].

For reliable multi-criteria assessment of the process state, the STATISTICA and a software package called the DAQSYSTEM developed in LabVIEW environment were used to calculate 14 statistical and spectral features of the measured on-line signals [16].

To correlate the features of the measured on-line signals with the wheel waviness, after every second grinding cycle, the waviness of the WCS along the wheel circumference were measured with the aid of a specially designed measuring device [21]. The layout of this sensor is shown in Fig. 2. The grinding wheel was driven frictionally during measurements by the rotating workpiece which was provided with rubber rings on its outside diameter. A modified inductive LVDT sensor equipped with flat gauging slides made of leuco-sapphire crystal and the VIS amplifier were used for the measurements of waviness. The same driving principle was used for grinding wheel profile measurements. In this case the measuring head and the amplifier of the Carl Zeiss Jena ME-10 roughness sensor was used. The heads were mounted on a special slide which allowed precise positioning of the wheel profile perpendicularly to its circumferential surface in parallel direction to the vector of grinding wheel rotational speed.

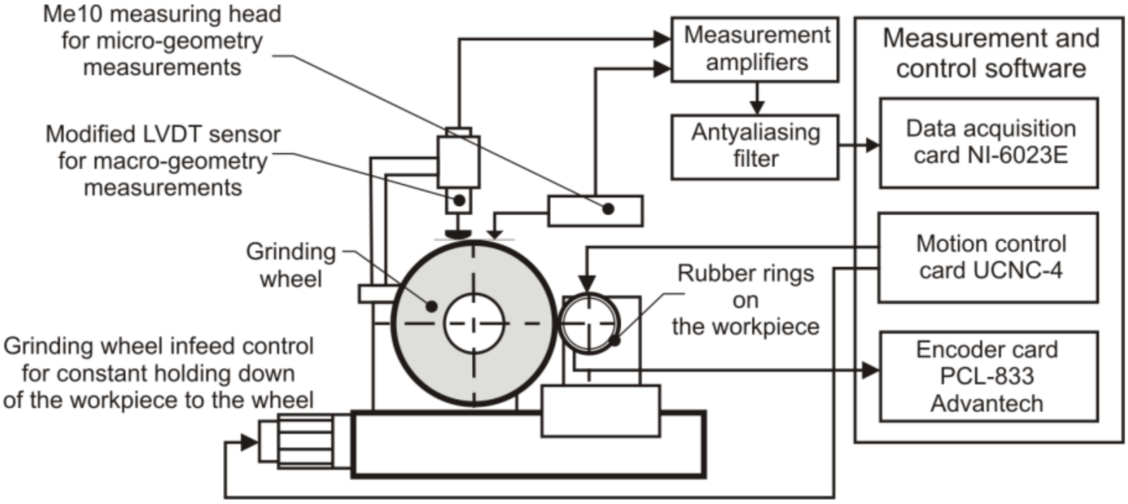

Fig. 2. Layout of the grinding wheel surface profile and waviness sensor

These measurements were made in off-line mode because possibilities of an on-line measurement of the wheel waviness are very limited in practical applications. A spectral analysis of the measurements made with the aid of DAQSYSTEM allows an assessment of waviness of the wheel to be performed.

The collected data consists of 78 objects which are grinding process samples diversified with respect to the specific material removal rate Q'_w, the speed ratio q and the wheel cutting ability represented by the specific material removal V''_w since the last wheel dressing. There are the 3 input conditions for each of the 78 grinding samples. Each object embodies a single sample of grinding process working cycle characterized by the 14 measured signal features and the assessment of waviness of the wheel measured after each grinding test.

3.3. DETERMINATION OF THE WHEEL WEAR SYMPTOMS

Selection of the features which are best-correlated with the grinding wheel waviness from among the 14 calculated signal features was an important issue in the presented research, especially because of the great number of the signal features (14) in relation to the number of samples in the collected data set (78). The applied prediction oriented, iterative approach to the reduction of feature number was generally based on the concept of reducts used in the DRSA applications. The detail description of this methodology is presented in [16]. As a result of the feature selection, the following 5 features were chosen as the symptoms of the wheel wear propagation process:

- C1 - vibration signal average power spectrum in the range 600-1000 Hz,
- C2 - vibration signal average power spectrum in the range 1200-2000 Hz,
- C3 - entropy of the vibration signal wavelet components in the range 1875-2500 Hz,
- C4 - entropy of the EARMS signal wavelet components in the range 625-1250 Hz,
- C5 - variation coefficient of the EARMS signal.

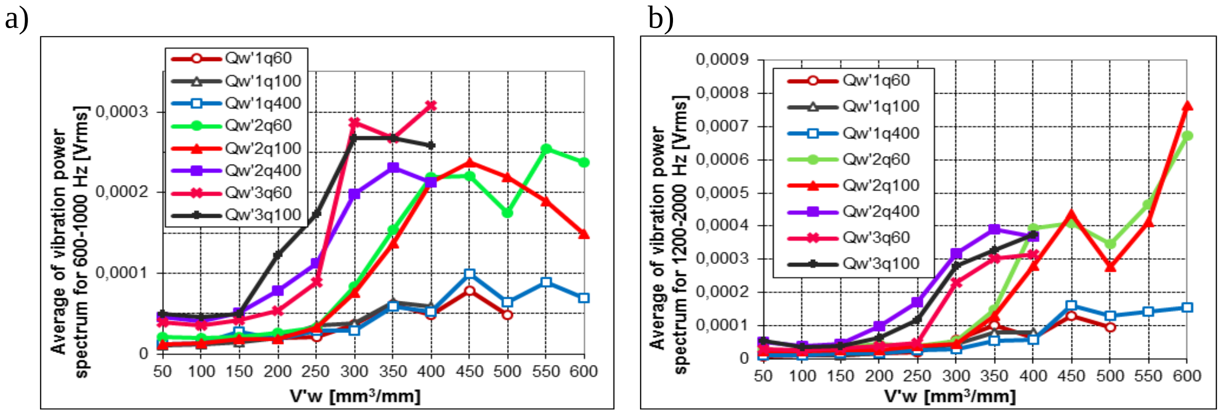

Fig. 3. Change of the power spectrum average value as a function of the specific material removal in the frequency range of: a) 600 – 1000 Hz, b) 1200 – 2000 Hz

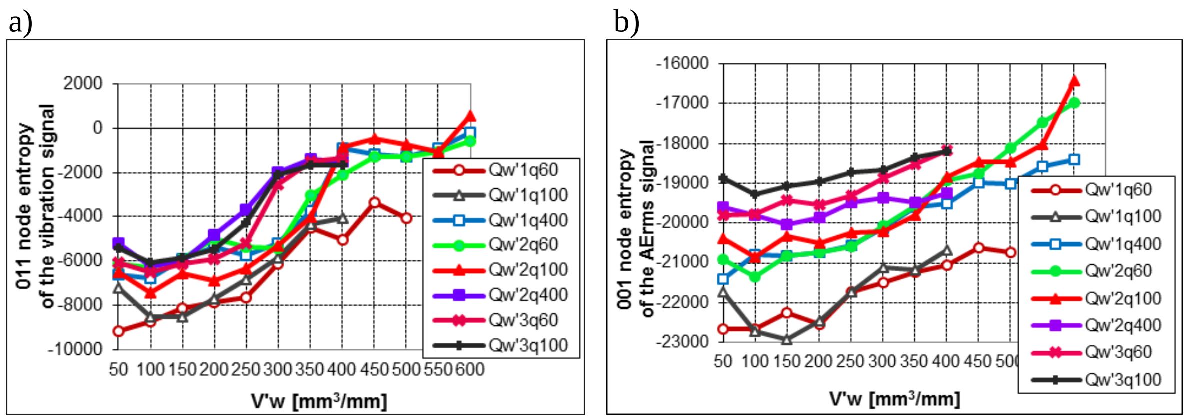

Fig. 4. Change of the entropy of the wavelet coefficients as a function of the specific material removal: a) in the frequency range of 1875-2500 Hz for the vibration signal, b) in the frequency range of 625-1250 Hz for the of the AE RMS signal

The first 4 chosen symptoms of the wheel waviness development are results of the Digital Fourier Transform (DFT) and the Packet Wavelet Analysis (PWA) used as the processing methods for feature extraction from vibration, the raw AE and the root mean square (RMS) value of AE signals. All of them presents power spectrum measures of these signals in two similar ranges of frequency: around 600 to 1250 Hz and the range of about twice higher frequencies. They are very alike in their course as functions of the specific material removal (Fig. 3 and 4). It was checked that these frequency ranges include the natural frequencies of the ground workpiece and the machine spindle headstock [22]. It confirms that the chatter frequencies are close to the natural frequencies of the machine-workpiece-wheel system.

A spectral analysis of the wheel waviness measurements allows an assessment of waviness and out-of-roundness of the wheel to be performed. The harmonic components appearing in the measured profiles correspond to different frequencies of waves on the wheel circumference. The highest amplitudes appeared in the range of 10-50 waves per wheel circumference. Thus, the average amplitude of the DFT power spectrum of the wheel circumference profile in this range was used as a measure of the WCS waviness (Fig. 5). The DFT analysis shows that the WCS waviness, being a result of the chatter regenerative effect on the wheel, is a good indicator of the WCS macro-geometry state.

To measure the strength of the linear relationship between the grinding WCS waviness and the power spectrum average value of vibration, as well as the energy of the applied wavelet decompositions in the both frequency ranges, the correlation coefficients between these variables as functions of the specific material removal were calculated. In most cases the coefficient values exceeded 0.9.

4. THE PROPOSED PREDICTIVE ANN MODEL OF THE GRINDING WHEEL RUL

4.1. THE NETWORK TRAINING

As described in the section 3.2, the collected data base consists of 78 grinding samples grouped into 8 series. Each series represents a number of cycles performed with given combination of Q'_w and q and completed to the point at which the state of the grinding process was recognized as unmanageable because of appearance of such phenomena like huge vibrations or workpiece surface burn. For this reason, depending on the applied parameter combination, the individual series consist of 8 to 12 grinding cycles that were 400 to 600 mm^3/mm of the specific material removal and for each series this a higher volume than the recommended grinding wheel life. It means that to establish the data set for network training, validation and testing, the collected number of grinding samples in each series has to be limited to those for which the highest specific material removal V''_w is smaller than the value related to the recommended value of criterion assumed for the grinding wheel life. The average amplitude of the DFT power spectrum of the wheel circumference profile in the range of 10-50 waves per wheel circumference as this criterion was adopted for this research in section 3.3. Taking into account the state of the art in grinding technology, the value of 0.025 (V_{RMS}) was implemented as the threshold of this amplitude limiting the wheel grinding life. This is illustrated in Fig. 5.

The wheel lives for each combination of grinding parameters resulting from the wheel threshold amplitude and the resultant overall number of data samples for the network training, validation and testing are presented in Table 1. Having the data set created as it is shown in Table 1, the MATLAB Neural Network Toolbox 2017 was used to developed an ANN based model of grinding wheel remaining useful life. The structure of this model is discussed in section 2 and illustrated in Fig. 1.

After many training trials an optimal network was established. It comprises 14 neurons in the input layer, 10 neurons in the hidden layer and the out layer with one output returning the grinding wheel RUL.

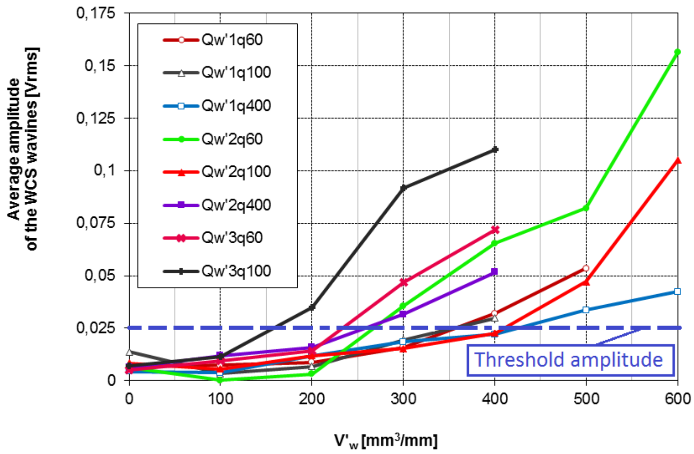

Fig. 5. Wheel average waviness in the range of 10-50 waves per wheel circumference as a function of the specific material removal and the threshold amplitude for the wheel life

Table 1. The wheel lives and the resultant number of data samples for each combination of grinding parameters

Grinding conditions & wheel life	Specific material removal inspection points [mm^3/mm]							No of samples
	100	150	200	250	300	350	400	
$Q'_w 1;q60$ L=355	X	X						5
		X	X					
			X	X				
				X	X			
					X	X		
$Q'_w 1;q100$ L=355	X	X						5
		X	X					
			X	X				
				X	X			
					X	X		
$Q'_w 1;q400$ L=429	X	X						6
		X	X					
			X	X				
				X	X			
					X	X		
						X	X	
$Q'_w 2;q60$ L=269	X	X						3
		X	X					
			X	X				
$Q'_w 2;q100$ L=410	X	X						6
		X	X					
			X	X				
				X	X			
					X	X		
						X	X	
$Q'_w 2;q400$ L=259	X	X						3
		X	X					
			X	X				
$Q'_w 3;q100$ L=237	X	X						2
		X	X					
$Q'_w 3;q60$ L=159	X	X						1
Total number of samples for network training								31

The 31 grinding samples of data set were randomly divided as follows: 21 samples to the training set, 5 samples to the validation set and 5 samples to the testing set. The Levenberg-Marquardt (LM) algorithm was used to learn the network.

4.2. DISCUSSION OF RESULTS

The performance of the obtained network can be analyzed using two plots. The first plot presents the mean square errors in function of the training epoch number for training, validation and testing procedures – Fig. 6.

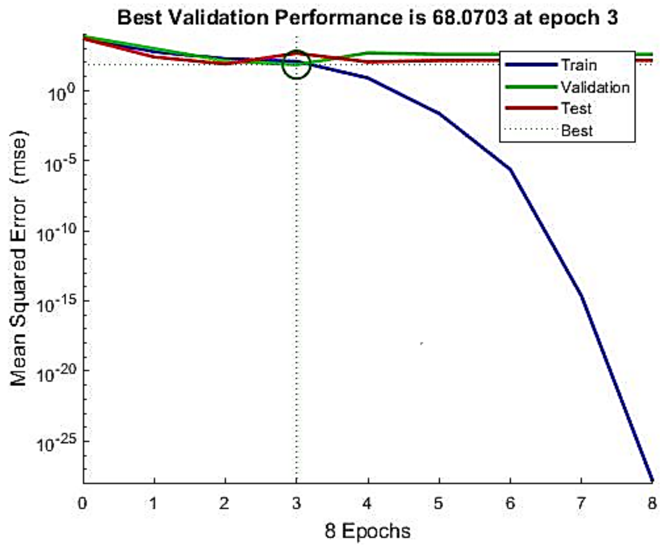

Fig. 6. Change of the mean square errors for training, validation and testing procedures

The plot shows that at the third epoch validation performance reached a minimum. The course of validation and training curves are very similar to the third epoch. Starting from this epoch the validation curve begins to rise and the training performance rapidly decreases what means that the network begins to over fit the training data. This is the moment when the training should be stopped and the weights and biases obtained the optimal values. Summarizing, the learning process of the obtained network proceeded properly.

The next method of network validating are regression plots, which show the relationship between the outputs of the network and the targets – Fig. 7. The individual plots show the correlation between outputs and targets for training, validation, testing and for training, testing and validation together. The values of linear regression coefficients for all the plots are higher than 0.9. It means that the obtained network possesses a good capability for data generalization. The prediction results obtained with the developed grinding wheel RUL model are shown in Table 2, where the target lives, predicted lives and prediction errors are percentage of the target full wheel lives for the individual samples in the training data set.

The RUL prediction results show that the overall average prediction error is equal to 10.82% of the target full wheel lives for the individual samples in the data set. There are 5 cases when the RUL of wheel is longer than those really reached. It can be to some extent dangerous for the quality of the ground surface, especially when the predicted life is higher than 120% of the real one what takes place for the 16th sample. But this grinding sample is specific because its course of the wheel waviness increase is significantly flat (Fig. 5).

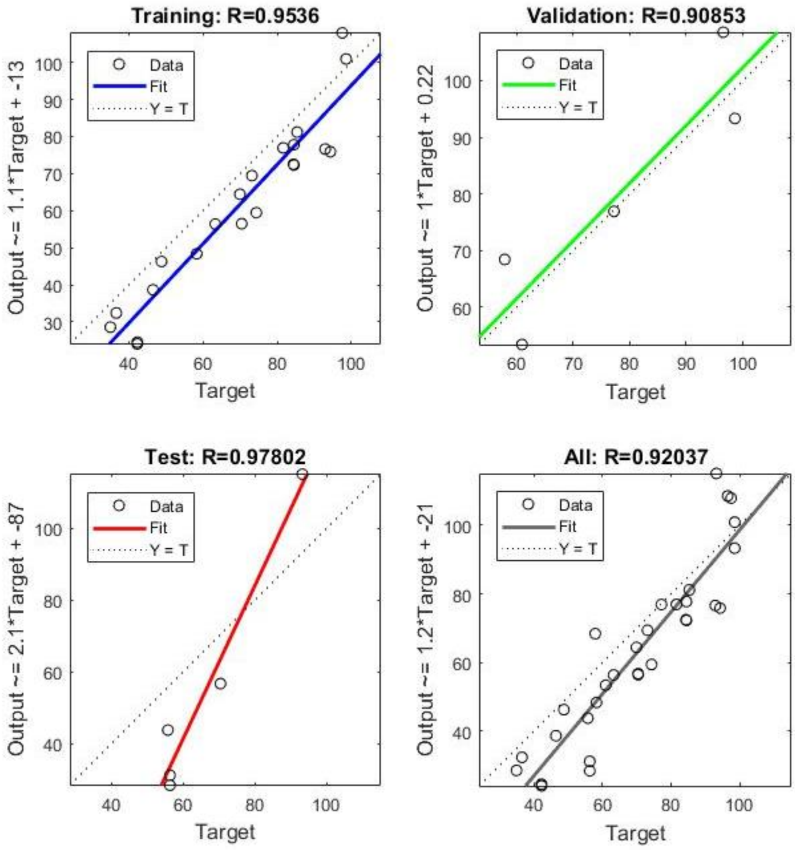

Fig. 7. Regresion plots of the network

Table 2. The RUL prediction results

No of sample	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Target Life %	42.25	56.33	70.42	84.51	98.59	42.25	56.33	70.42	84.51	98.59	34.97	46.46	58.28	69.93	81.59	93.24
Predicted Life %	24.06	28.44	56.75	72.29	100.9	24.53	31.22	56.47	77.78	93.33	28.57	38.64	48.36	64.43	76.94	115.1
Prediction error %	18.19	27.89	13.67	12.21	-2.33	17.72	25.11	13.95	6.73	5.26	6.40	7.82	9.92	5.50	4.65	-21.8
No of sample	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	-
Target Life %	55.76	74.35	92.94	36.57	48.78	60.98	73.17	85.37	97.56	57.92	77.22	96.53	63.29	84.39	9434	-
Predicted Life %	43.80	59.45	76.61	32.39	46.27	53.39	69.44	81.18	107.9	68.42	76.92	108.6	56.37	72.51	75.88	-
Prediction error %	11.96	14.90	16.33	4.14	2.51	7.59	3.73	4.19	-10.4	-10.5	0.30	-12.0	6.92	11.88	18.46	-

For most of the data set samples (for 26 from 31) the predicted wheel lives are shorter than their target lives. Such results are better from the point of view of the required workpiece surface quality although if the error is bigger than 20% the results are unsatisfactory from a cost and productivity perspective. But it occurred only in 2 data set samples. For 14 grinding samples, the predicted wheel lives were smaller than the target lives by less than 10%. Such a distribution of the results are difficult to explain because neural network models are “black box” models so it is impossible to analyze qualitative influence of the individual inputs on the network output.

It seems that in the presented application, the structure of the network plays the most important role. Because the inputs are the measures identifying the wheel condition at the current inspection point and those at the previous point the output strongly depends on the increase of waviness for the succeeding inspection points especially for the late in the wheel life inspection points. Thus taking into account significant differences in distances between the inspection points and the end of the wheel life for the individual samples and the relatively small number of training samples, the obtain RUL prediction errors can be recognized as satisfactory.

5. CONCLUSIONS

In the paper, an ANN based model of the grinding wheel RUL prediction is developed. The model uses the wheel life period values and the values of the features chosen as symptoms of the wheel condition as well as two basic grinding conditions as inputs. The output of the network is the value of the wheel life period achieved at the current inspection point expressed as the percentage of the full life period achieved for this grinding sample. The amplitude of the wheel waviness was proposed as the criterion of its wear. The value of 0.025 (V_{RMS}) was implemented as the threshold of this amplitude limiting the wheel grinding life. The ANN was trained using 31 samples of grinding selected from 78 grinding data samples according to the above assumptions. Five features extracted from measured signals correlated with the changes of the wheel waviness were chosen as the symptoms of the wheel wear propagation process and used in the training data set. The MATLAB Neural Network Toolbox 2017 was used to developed the ANN model. To overcome the network overfitting problem, the Levenberg-Marquardt (LM) algorithm was used to learn the network.

The results of the grinding wheel RUL prediction can be characterized by the obtained overall average prediction error. It is equal to 10.82% of the target full wheel lives for the individual samples in the training data set. Taking into account properties of the data set used for the model training, the obtain RUL prediction errors can be recognized as satisfactory. The obtained results indicate that the prediction ability of the ANN model can be increased when the late in the wheel life inspection points will be use for the model training and, as always in the case of neural models, the number of training samples will be higher. The presented ANN approach to predictive model building seems to be promising. However, one of the biggest weakness of the ANN models is the lack of knowledge about the confidence level of the prognosis output what is a significant obstacle in practical applications of this type of RUL models, especially in the context of the CPSs requirements. Thus, this problem provides an objective for future research.

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