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On burr height estimation based on axial drilling force

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ABSTRACT

Purpose: The main goal of the research is to build a model of relationship between burr height created during drilling operation and signal representing axial drilling force. Such a model can be applied in diagnostic system for on-line estimation of bur height.

Design/methodology/approach: The first applied approach is based on a step by step procedure in which several statistical models were built. The second one is based on specific features of artificial intelligence methods. The artificial neural networks serve as a tool for data selection and integration while the fuzzy logic systems are applied for data integration, only.

Findings: The developed algorithm for processing axial drilling force allowed constraining the noise inherent to the drilling process and emphasising the information that could be useful for building considered model. The impact of the properly conducted data selection has been emphasised. Also, importance of providing information represented with axial drilling force has revealed.

Research limitations/implications: The developed models need to be checked or improved for practical implementation. Such improvement can be done by introducing other signal features or other cutting parameters as model inputs. Also, analysis of other signals that can be measured during drilling is assumed as a future work.

Practical implications: The conducted research reconfirmed possibility of on-line diagnostics of bur height during drilling. Several parameters necessary for such diagnostics have been estimated. This suggests continuing the research in order to design a system that could be applied in industrial conditions.

Originality/value: The proposed approach is not a typical since analytical models, FEM models or models basing only on cutting process parameters have been considered, mainly. Such models are limited to two dimensional machining, usually. Besides, application of artificial intelligence methods for data selection and integration points at novelty of the research conducted.

Keywords: Machining; Burr formation in drilling; Diagnostics; Artificial intelligence methods

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1. Introduction

It is widely known, that burrs which are created in most machining operation deteriorate quality of the part, cause difficulty in part assembly and may cause safety hazards (Fig. 1). These undesirable features of burrs justify a need for some means allowing avoiding such cases. Frequently, deburring operation is performed, e.g. [2, 6]. However, this operation should be carefully considered, since the deburring cost can be as high as 30% of the cost of production. Therefore, one can try to find another way to reduce the negative influence of burrs. In this case, burr formation

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models can be applied in order to reduce burr size in a certain type of machining. Application of such models consists in finding nearly ideal machining conditions, improving part design or conducting process planning for proper burr placement (easier to deburr). From other hand, on-line workpiece diagnostics would be desirable in order to estimate the created burr size and decide whether deburring operation is necessary.

The paper deals with above mentioned burr diagnostics. The presented research has been initially described in [9]. Then, several approaches have been tested, e.g. [8]. Finally, the recorded data has been again processed and a specific, new approach has been proposed. This is reflected in structure of the paper in which author tries to summarise research conducted since several years.

Regarding the burr formation phenomenon, it should be emphasised that a lot of work has been done, already. Especially, the research conducted by Consortium on Deburring and Edge Finishing (CODEF) [2] introduced many interesting solutions and findings. Following this research, the problem of burr formation models can be regarded from different points of view. Generally, the two types of models are taken into consideration. In the first case, analytical models based on the cutting process mechanism are analysed. The models require understanding of the properties and characteristics of burrs produced by manufacturing process, e.g. bending and shearing during chip formation must be analysed in relation to characteristics of workpiece material. The earliest models basically applied the theory of plastic deformation for assumed orthogonal cutting conditions, e.g. [1]. Some enhancement to the models can be introduced by considering the plastic hinge concept. However, this approach focuses only on the two dimensional machining case. Machining operations such as face milling are not strictly two dimensional and hence these models are not applicable. In the case of three dimensional machining, the finite element method (FEM) seems to be a prime candidate to predict burr size [2].

The second type of models takes in to consideration empirical data. In this case, modelling is performed with use of statistical methods that potentially allow representing a certain burr characteristic value as a function of cutting parameters. Next, information acquired by measuring and analysing selected signals recorded during cutting process can be applied, as well. The research presented in the paper deals with such an approach. The main goal of the research is to build a model of relationship between burr height created during drilling operation and signal representing axial drilling force . This approach requires several assumptions that must be established in order to decide which measured signal feature can be applied and how to pre-process the measured signal. Since a lot of combination can be considered in this case, the two possible procedures are discussed in the paper. In the first case, we applied a step by step procedure in which several models were built and compared. This comparison allowed finding a set of parameters (i.e. parameters of signal processing methods and signal features) that gave burr height models with high criteria values. The second procedure aimed at performing the search for optimal parameters in more „automatic” way, i.e. with reduced human interaction. This procedure is based on specific features of artificial intelligence methods. In this case, artificial neural networks and fuzzy logic systems are considered. The artificial neural networks, namely Feed Forward Back Propagation (FFBP) neural networks serve as a tool for data selection and data integration while the fuzzy logic systems are applied as an alternative method for data integration, only. Here, the Mamdani type of fuzzy reasoning is tested.

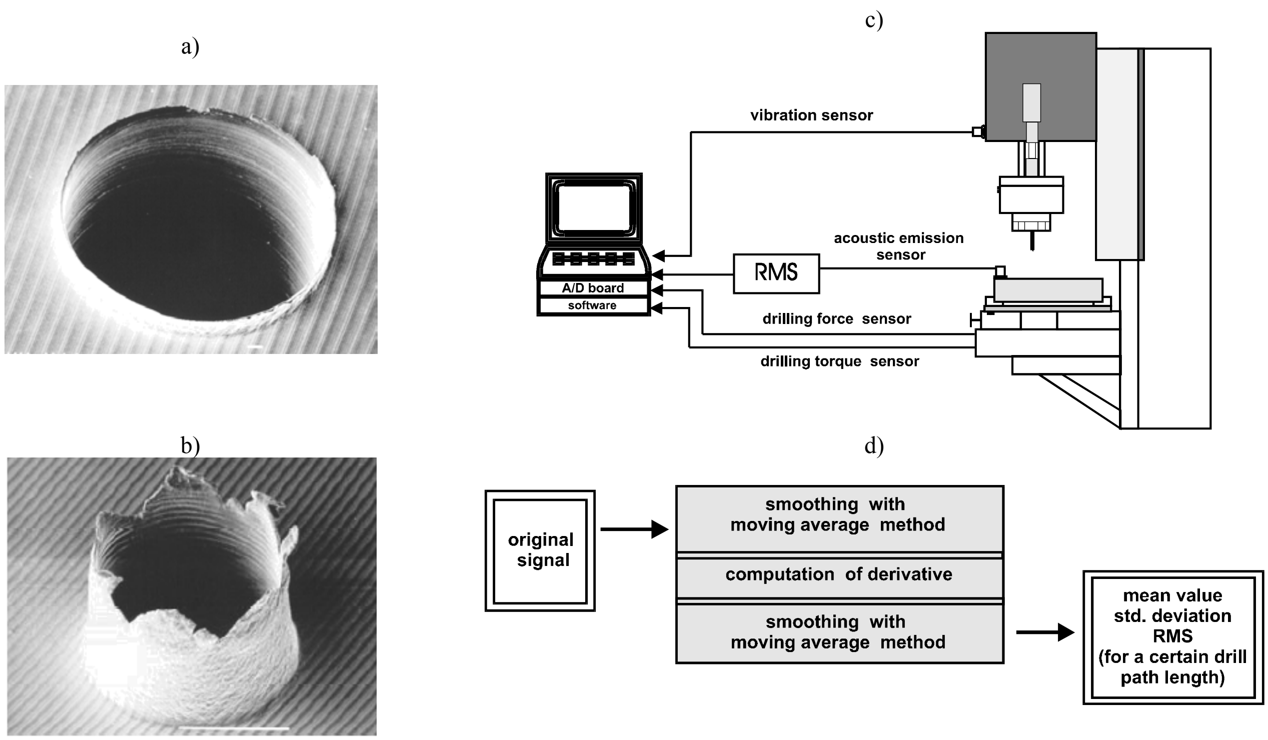

Fig. 1. Examples of drilling burr shapes; uniform (a) and crown (b) burrs [4]; schematics of the measuring set-up (c) and block diagram of the measured signal processing

2. Experimental procedure

The measurements were conducted while drilling austenitic steel 00H18N10 on drilling machine tool WRS-25/08 (Fig. 1c) [9]. In order to perform drilling, twist drills diameter of 5 mm were applied. The drills varied according to their geometrical parameters and cutting edge wear. Also, the experiments were conducted with different cutting speeds. The mentioned above varying parameters were as follows:

- straight and corrected cutting edge (pks/kks);
- chip clearance angle of 23^0 and 33^0 (λ);
- rotational speed 764 rpm (v_C=12 m/min), 637 rpm (v_C=10 m/min) and 892 rpm (v_C=14 m/min);
- new drills and drills with average wear VB = 0.57 mm.

The four signals were measured during each drilling operation, i.e. axial drilling force, torque, vibration and acoustic emission. However, in the paper the axial drilling force measured with Kistler dynamometer is analysed, only. This was decided basing on careful analysis of the recorded signals. After each operation, the burr height was measured with a dial gauge. For each drilled hole, the burr height was measured in three points (120^0) along the hole edge and an average burr height was calculated. Generally, 96 experiments were conducted, i.e. for each combination of the above mentioned parameters, four holes were machined.

The general assessment of the conducted experiments was aiming at finding the parameters that affect the burr height. Reviewing the results of the experiments it has been found out, however, that only qualitative assessment could be done. Such a case was caused by a strong variation of burr height even while drilling with the same parameters. Trying to underline the most significant parameters, one could point at the cutting edge wear that caused substantial increase in burr height. Also, increase in cutting speed caused an increase in burr height. In contrary, influence of other parameters depended one on another. These findings can be used to not only characterise changes of burr height but to confirm a need for observing sensor signals in order to estimate burr height. In other words, it can be concluded that in the discussed case, burr height modelling cannot be done using the drill parameters and the cutting parameters, only.

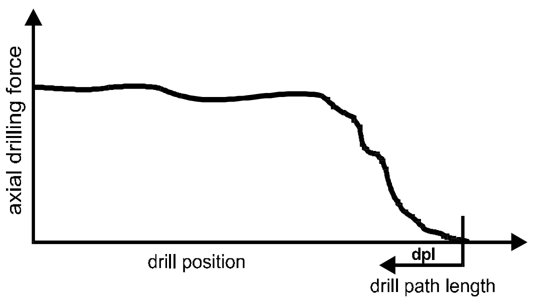

Fig. 2. Determination of the drill path length „dpl"

As it was mentioned above, the measured signal representing the axial drilling force was analysed in order to estimate the burr height. The analysis focused on two main tasks. In the first case, the drill path length „dpl" (Fig. 2) was to be decided. This length describes a position of drill tip from which the cutting force potentially contains important information related to burr formation. The second case is related to measured signal processing methods. In our research, it was assumed that burr height is related to force changes while drill exits the workpiece. Therefore, it was decided not to observe the original signal but its derivative. Next, it was assumed that the observed signal can be smoothed with moving average method before and after calculating the derivatives (Fig. 1d). Such approach should allow to constrain influence of fast changes of the cutting force that do not show any relation to burr formation. Finally, it was decided that three processed signal features would be analysed, i.e. RMS value, mean value and standard deviation. Generally, the described above assumptions make it necessary to decide about the drill path length and the parameters of the moving average method, i.e. smoothing window widths. Also, a processed signal feature that shows the highest correlation to burr height should be pointed at. The results of burr height estimation based on selected features of axial force signal processed with different parameters are presented in the next sections of the paper.

3. Burr height estimation — conventional approach

Following the assumptions stated in the previous section of the paper, several tests have been conducted. In order to constrain the number of tests, the signals measured while drilling with cutting speed of 12 m/min were analysed, first. It was assumed that the results obtained from this part of the research would be applied for analysing the whole available data. Each test consisted of three steps. In the first step, the measured drilling force signal was processed with a certain signal processing method (Table 1). The signal processing methods varied according to smoothing window widths. Then, for each of nine drill path lengths, the mean value, RMS value and standard deviation were calculated. In the last step, model building procedure was applied to build a model of relationship between burr height and calculated feature (e.g. Fig. 4). Type of the models was decided following an observation of data distribution. Mainly, exponential or 2 order polynomial models were tested. The quality of the models was assessed based on the correlation factor R and the sum of the square residual values SRV.

Table 1.
Schematic schedule of the tests conducted

	A	B	C
D	To =0.097 Tr =0.000	To =0.097 Tr =0.097	To =0.097 Tr =0.195
E	To =0.195 Tr =0.000	To =0.195 Tr =0.097	To =0.195 Tr =0.195
F	To =0.389 Tr =0.000	To =0.389 Tr =0.097	To =0.389 Tr =0.195

T_o [s] - smoothing window width applied to process the original drilling force signal;
T_r [s] - smoothing window width applied to process the derivative of the original drilling force signal;
For each T_o and T_r , nine drill path lengths „dpl" were analysed (from 0.57 mm to 3.23 mm).

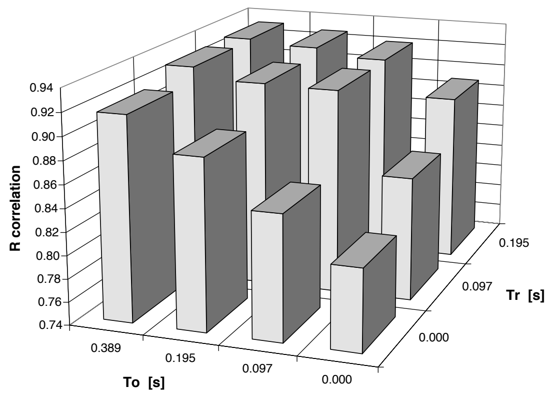

Fig. 3. Exemplary influence of smoothing window widths T_o and T_r on correlation factor R

As it can be seen from Table 1, nine tests were conducted for each combination of smoothing window widths. The highest R value and the lowest SRV value pointed at the drill path length that could be considered as optimal. Such approach means that for a certain measured signal feature, 81 models had to be built in order to decide about the smoothing widow widths and the drill path lengths. At the next step, the R and SRV values corresponding to the optimal drill path length were presented in the form of graphs, shown in Fig. 3. From this figure it becomes obvious that R approaches the optimal values while T_o and T_r reach 0.389 s and 0.195 s respectively. Increasing window widths above these values does not improve the models in terms of R and SRV values.

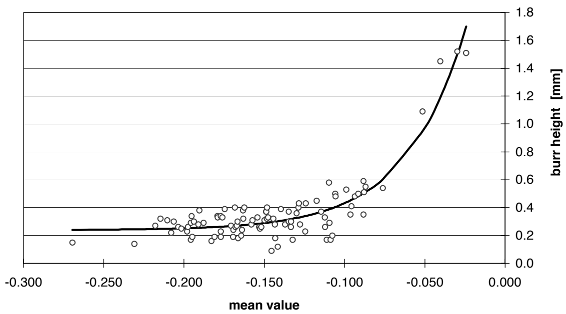

Fig. 4. Burr height versus mean value of processed derivative of axial drilling force [9]

The above described results were based on analysis of RMS values calculated for processed drilling force signal. The next part of the research aimed at comparison of models built with use of two other features, i.e. mean value and standard deviation. In order to perform such a comparison the similar procedure was applied as in the case of RMS values. The obtained results revealed that the best model in terms of R and SRV values could be achieved based on the mean values of the processed drilling force signal. In this case R=0.950 and SRV=0.205 were obtained for the drill path length of 1.52 mm. The same drill path length was selected while analysing models based on RMS values and R and SRV were as follows : R=0.931 and SRV=0.287. In contrary to the analysis of the RMS and mean values, the models built with use of the standard deviation values gave poorer results and were, therefore, discarded.

The last stage of the conventional approach consisted in testing the data collected while drilling with cutting speed of 10 m/min and 14 m/min. The main task to be solved at this stage was to estimate the optimal drill path length for these cutting speeds. Following the main procedure, a next set of models was built and analysis of R and SRV values was performed. The analysis confirmed that previously determined smoothing window widths can be applied for different cutting speeds. However, the drill path lengths depend on the cutting speed and must be determined independently for each cutting condition. For the cutting speeds applied in the experiments the optimal drill path lengths were estimated as follows: dpl=1.27 mm for 10 m/min; dpl=1.52 for 12 m/min and dpl=2.22 mm for 14 m/min. The estimated values were, then, applied to build burr height model for whole available data. Such a model is shown in Fig. 4. This model expresses a relationship between burr height and mean values of the processed drilling force signal. In the case of the model from Fig. 4, R and SRV values were of 0.926 and 0.800 respectively. As it could be expected, the models based on RMS values gave lower criteria values (R=0.906 and SRV 1.014).

A partial summary of the conducted research can be done taking into consideration two main points. In the first case, it is concluded that the applied procedure allows suppressing much of the noise inherent to drilling process and emphasises the information which is related to burr formation. This can be expressed in terms of final models built for whole available data and relatively high correlation factor R and low SRV values. However, the way in which the final models were obtained cannot be considered satisfying. As it has been shown above, one would have to spend a lot of time in order to test high number of models to point at the best parameters of signal processing methods and the optimal tool path length. Thus, it would be desirable to perform such a search in a more „automatic" way. This means that in the next part of the research we try to apply and test a certain procedure that potentially allows automatically selecting measured signal features which show the highest correlation to the observed phenomenon.

4. Application of artificial intelligence methods for data selection and integration

Following the conclusions stated in the previous section, Feed Forward Back Propagation (FFBP) neural network, has been applied to select parameters of the signal processing methods and optimal drill path length. Application of FFBP network is based on the procedures and methods available in the Intelligent Monitoring System Designer (IMSD) described in [7, 10, 11]. IMDS is a tool that provides facilities, i.e. methods and algorithms, to automatically perform design of monitoring systems. The main idea applied in this system is to try to retrieve the most significant features of artificial intelligence methods, i.e. artificial neural networks, fuzzy logic systems and evolutionary algorithms. It should be added that conventional approaches are implemented in IMDS, as well. Regarding application of artificial intelligence methods, capability to extract important and useful information from input data should be emphasised since data selection is one of major tasks considered in the paper. This can be done with artificial neural networks by evaluating the weights between input and hidden layers in order to detect inputs that do not show a sufficient contribution to the computation of the actual output values, e.g. [11].

The three feature selection methods basing on FFBP neural network have been tested for this application [7, 11]. The first one is called weight pruning method. The weight pruning method examines each weight of already trained network and tries to eliminate some of them based on maximum and RMS errors. Eventually, each input to the network is described with the number of weights that did not „survive" the process of elimination. It is assumed that the higher this number is, the less important is the respective input. The second method is called weight sum method. The method is also applied to the already trained neural network. Importance of each input is estimated based on the sum of absolute values of weights outgoing from this input. The inputs with small weight sum are considered as less important and, therefore, can be dropped. It can be added that the small weight sum value means that considered input was not "intensively" trained because it did not contribute to final output value determination, i.e. is less important. The third approach takes into consideration sensitivity analysis (sensitivity method). In this case, after the network is trained, the sensitivity of each output with respect to each input is individually calculated for every training vector. In order to assess the importance of each input, the root-mean-square value of the obtained sensitivities is, then, computed. Finally, the input importance is scaled within the range 0.0 - 100.0 % .

The feature selection methods have been applied in the way that corresponds to the approach performed in the case of the conventional analysis. As it was described, determination of the optimal drill path length was one of the most important tasks. In order to determine drill path length, several models had to be built first. Then, R and SRV values had to be examined. Typical representation of such a case is shown in Fig. 5a from which one could find out that the drill path length of 1.52 mm seems to be optimal. Application of the input selection methods should not involve a step by step (model by model) analysis. Therefore, all values representing different drill paths lengths were fed to the 9-3-1 FFBP network and the training was performed. Then, the importance of each input was estimated, as shown in Fig. 5b.

The obtained results correspond to those obtained in the case of the conventional approach (). The input selection methods point at these drill path lengths that gave the highest R and lowest SRV values. It is necessary to emphasise that the application of feature selection methods allows avoiding building and analysing of several models. Such a case is obviously interesting and desirable from a user point of view.

a)

b)

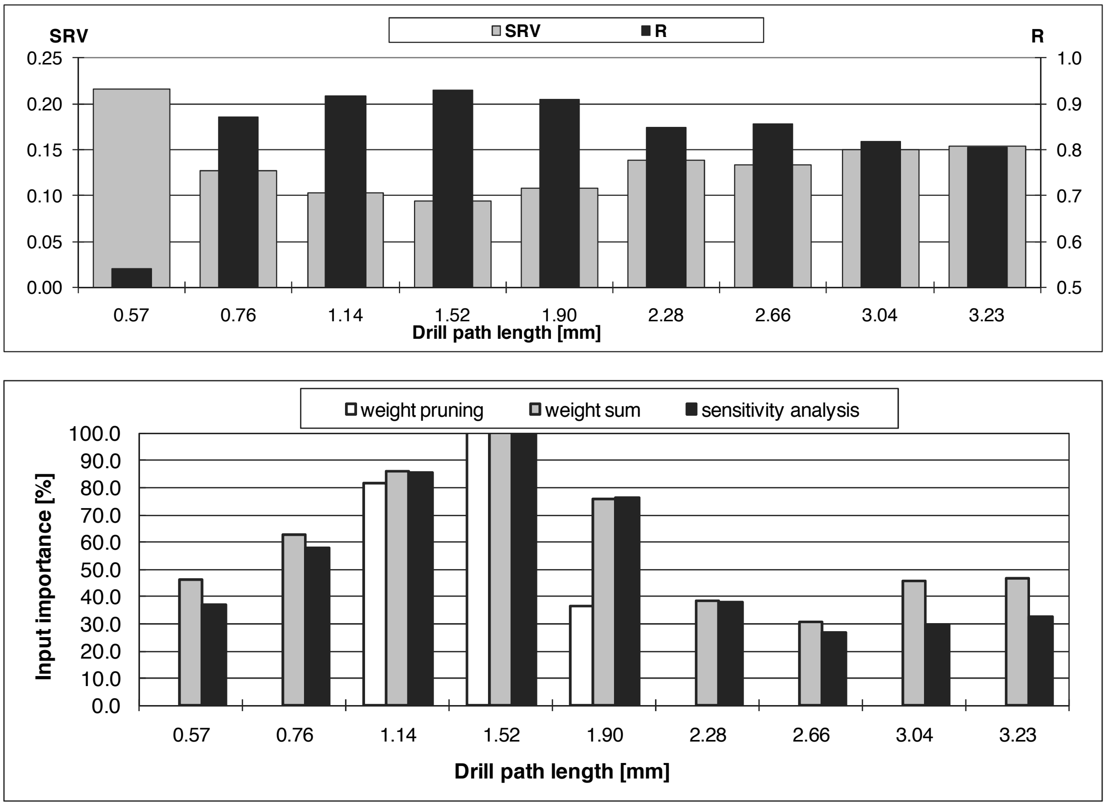

Fig. 5. Results of the conventional approach and FFBP neural network application for the case CF - Table 1, v_C=12 m/min; a) - R and SRV determined for burr height model basing on RMS values; b) - importance of RMS values estimated with FFBP network

The tests described above were focused on partial tasks reflecting the way in which the conventional analysis has been performed, e.g. first the optimal drill path length has been selected and, then, different signal features were tested for this length. Ideally, such analysis should be performed in parallel so the selection of the optimal drill path length would not affect selection of the signal feature. This means that application of data selection for deciding about drill path length and signal feature at the same time would be a very desirable approach. From neural network point of view this means that FFBP network should be trained with input vectors containing values representing different drill path lengths and the three analysed signal features. Here, the network has a relatively difficult task to solve since it is expected to select few inputs out of 27 values.

In the first step of analysis of the obtained results a general assessment of a relative importance of signal features should be taken into consideration. As it has been revealed, the weight pruning and the sensitivity method can be considered as the most reliable methods. In both cases, the mean values and RMS values are ranked with higher importance than the standard deviation, as shown in Fig. 6. Especially, the sensitivity method ranked the inputs in a very distinct way. It is necessary, however, to add that this method tended some times to give a similar importance to few inputs. This means that results of sensitivity analysis method application cannot be repeatable in some cases.

In the second step of the analysis a selection of the drill path length has been performed. As it can be seen from Fig. 6, both methods estimated inputs corresponding to the previously selected drill path length of 1.52 mm with the highest importance. Next, sensitivity analysis method uniquely pointed at mean value as the most important input. This fully corresponds to the previously shown results, again.

In case of weight pruning method, the final decision on measuring signal feature requires some additional discussion. This method suffers from low resolution sometimes. This is caused by expressing data importance with number of weights connecting input and hidden layers. If number of weights is low, the weight pruning method allows assessing importance with only few values form the range 0.0 - 100.0 %. Consequently, one should carefully consider inputs with similar importance. This is a case from Fig. 6 where weight pruning estimated the mean value and RMS value with similar importance. In order to finally decide on input importance, the selected data should been again fed into the network and importance estimation should be repeated. Such approach assesses mean value with highest importance.

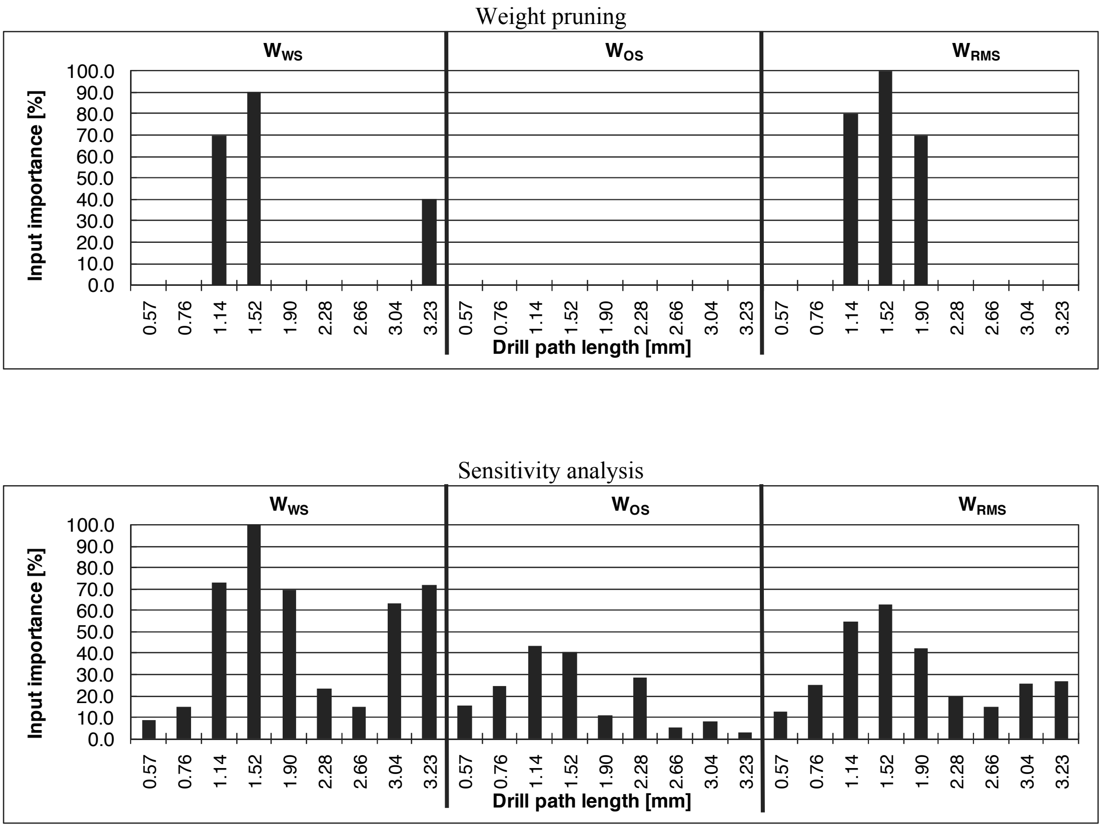

Fig. 6. Input importance estimated with FFBP neural network, W_{WS} – mean values, W_{OS} – standard deviation, W_{RMS} – RMS values, case CF - Table 1, v_C=12 m/min

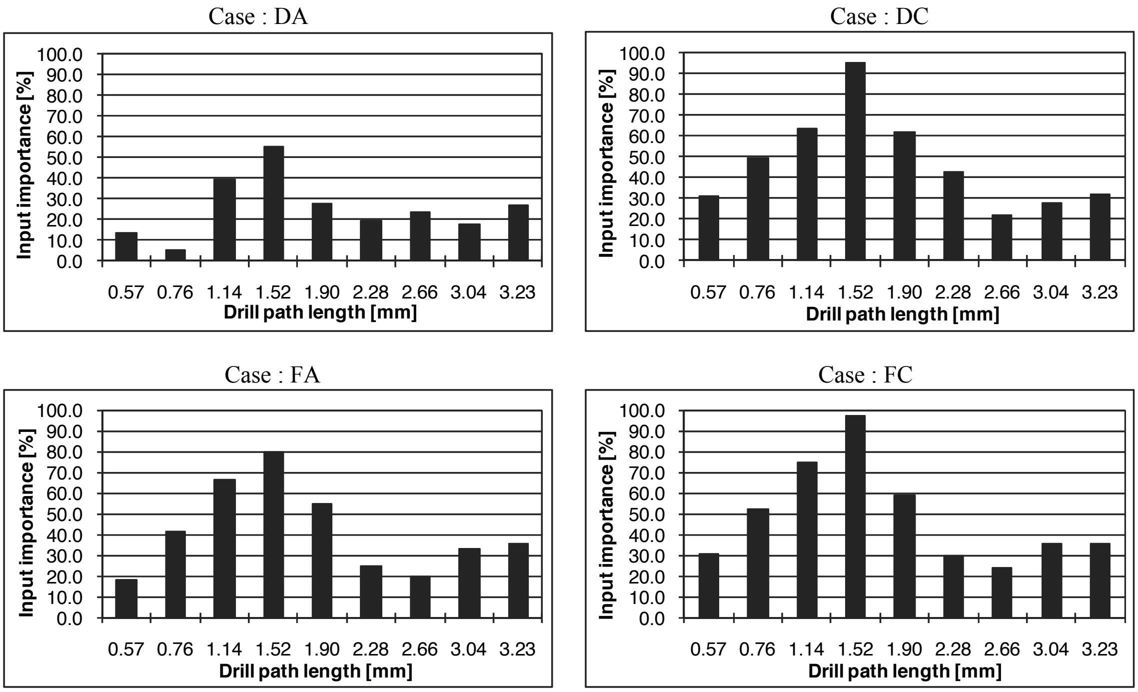

Fig. 7. Feature importance estimated with FFBP network fed with 81 inputs representing RMS values; selected cases from Table 1, v_C=12 m/min, importance estimated with the weight sum method

a)

b)

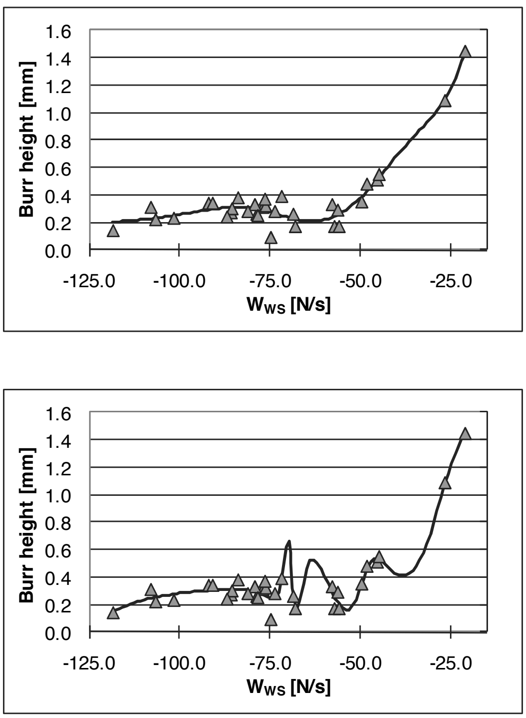

Fig. 8. A typical model obtained with FFBP neural network (a) and corrupted model built with improperly decided structure of FFBP neural network (b), case CF - Table 1, v_C=12 m/min

The most general case which was analysed with FFBP neural network consisted in selection of drill path length and the smoothing window widths. The selection was performed independently for each measured signal feature. This means that the network was fed with input vector representing 81 values, i.e. nine combination shown in Table 1 and nine drill path lengths for each combination. The results obtained in this case uniquely revealed that an increase in smoothing window widths increases the feature importance (Fig. 7). Also, for each combination from Table 1, the inputs corresponding to the previously selected optimal drill path length were estimated with high importance. However, additional neural network training is necessary in order to differentiate data importance, as it was described above. Similar case was observed while estimating importance of data representing the three considered cutting speeds at the same time.

Generally, it can be concluded that the input selection methods can be successfully applied to search for the optimal drill path length, the smoothing window widths and the measured signal feature. As a successful application we consider here an application which allows substantially decreasing time and effort spent for the analysis. This seems to be the case even if the network training is to be repeated.

Besides data selection, the model development can be performed with neural networks and fuzzy logic systems. It should be emphasised that application of these artificial intelligence methods is not necessary and serves for comparison purposes, only. A typical model obtained with application of neural network is shown in Fig. 8a. It must be underlined that the fuzzy logic system allows obtaining the similar model. The quality of the model depends on structure of both neural network and fuzzy logic system. For example, the quality expressed by correlation factor increases with increasing number of hidden nodes of neural network. However, if the parameters of neural network or fuzzy-logic system are not properly decided, substantially corrupted model can be developed. Such a case is shown in Fig. 8b. Here, the FFBP neural network contained large number of hidden nodes was trained. This large number of hidden nodes caused that the neural network model does not reflect the character of the analysed phenomenon.

5. Summary

Summarising the research presented in the paper the two assumed goals should be discussed. In the first case, an algorithm for processing axial drilling force has been developed. Developing such an algorithm we aimed at constraining the noise inherent to the drilling process and emphasising the information that could be useful for building a model of relationship between burr height and selected measured signal feature. The impact of the properly conducted data selection can be presented based on scatter diagrams that reflect model quality (Fig. 9). In Fig. 9a, scatter diagram representing model described with the 2 order polynomial is depicted. This model considers only selected cutting parameters, i.e. information on the state of cutting process expressed with measuring signals is not introduced. The second model basing on 4 order polynomial was developed with mean value of the processed signal of axial drilling force (Fig. 9b). The qualitative assessment of the two models already reveals the influence of information provided on-line by measuring signal. Satisfying correlation factor value of 0.964 was achieved in this case (Fig. 9b). Finally, we introduced cutting parameters and mean value of the measured signal into the model described with equation (1). Here, the correlation factor reached the highest value of 0.991 (Fig. 9c).

The above description is related to analysis of data recorded during drilling with cutting speed v_C=12 m/min. In the last step of the research, all available data was considered for burr formation modelling (Table 2). This approach fully reconfirmed conclusions and findings stated above. Also, artificial intelligence application can be justified based on results shown in Table 2.

$$H_Z = f_1(W_{WS}) + f_2(VB_{MAX}, \lambda, pks/kks) \quad (1)$$

$$H_Z = f_1(W_{WS}) + f_2(v_C, VB_{MAX}, \lambda, pks/kks) \quad (2)$$

where:
H_Z – burr height;
f_1 , f_2 - the 4 order and 2 order polynomial, respectively;
W_{WS} - mean value of the processed axial drilling force signal;
pks/kks - straight and corrected cutting edge;
λ - chip clearance angle;
v_C - cutting speed;
VB_{MAX} – maximal flank wear of drills applied.

Table 2.
Burr formation models and respective correlation factors

Model	R
H_Z=f(v_C, VB_{MAX}, λ, pks/kks), the 2 order polynomial	0.789
H_Z=f(W_{WS}), the 4 order polynomial	0.933
H_Z=f(W_{WS}, v_C, VB_{MAX}, λ, pks/kks), equation (2)	0.974
Fuzzy logic system with 5 inputs and 18 fuzzy rules	0.978
FFBP neural network, structure 5-3-1	0.984

The second goal of the presented research is related to the procedure applied for supporting the search for optimal parameters of signal processing methods. It is convenient to recall that we applied three feature selection methods based on FFBP neural network. The methods were expected to minimise time and effort that one would have to spend on reviewing of several combinations of analysed parameters. Based on the obtained results, some guidelines can be established in this case. Analysis of the recorded data must start obviously with calculations of different signal features for the signals processed with different smoothing widow widths. Then, the feature selection can be applied for assessing the influence of parameters of the signal processing methods (e.g.). At this stage, one can already try to estimate importance of drill path length. After deciding about smoothing window widths, an analysis of relative importance of different signal features and confirmation of drill path length selection can be performed. Eventually, the final decision on the selection of the optimal drill path length and the most promising measured signal feature can be done.

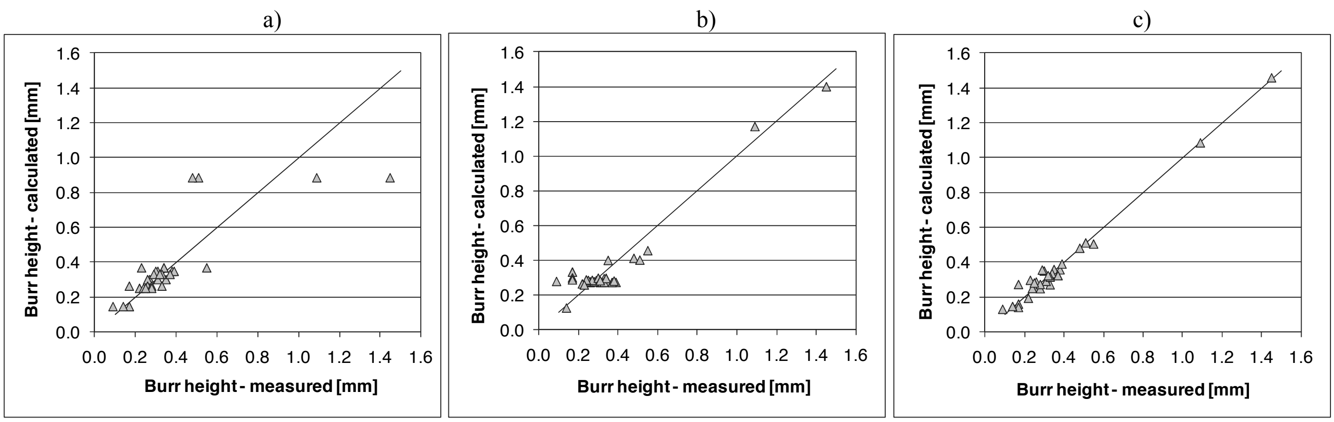

Fig. 9. Scatter diagram of the measured and calculated burr height; a) H_Z=f(VB_{MAX}, λ, pks/kks) model described with the 2 order polynomial; b) H_Z=f(W_{WS}) model described with the 4 order polynomial; c) H_Z=f(W_{WS}, VB_{MAX}, λ, pks/kks) model described with equation (1); v_C = 12 m/min, drill path length 1.52 mm, case CF - Table 1

The presented research should not be considered completed. It can be noticed that the developed models need to be checked or improved in the case of practical application for burr height estimation. Such improvement can be done in different ways. It seems reasonable to enhance the models by adding other signal features or introducing other cutting parameters as model inputs. Also, analysis of other signals that can be measured during drilling is assumed as a future work.

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