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A general ANN model of turning and its application for surface roughness estimation using acoustic emission signal

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Abstract

In this paper an application of ANN models are presented to estimate the roughness of a given finishing operation. The approach uses the acoustic emission sensor as an information source to improve the estimation capability of the ANN model. Building up the ANN model to avoid the problem of overlapping and non-invertible dependencies used a new approach. The model was built up and the roughness was estimated but further experiences are needed to improve this research using a larger number of training data.

Keywords: *Cutting process monitoring, Neural network, Surface roughness estimation*

1. Introduction

Several papers dealing with possible strategies of efficient monitoring of the cutting process can be found. A large number of them are based on the energy contents of the acoustic emission signal as described by Dolinsek [1]. In this paper the monitoring concept on the basis of sensing Acoustic Emission signals in finish machining processes was presented. From the contents of the AE signals they are able to extract significant features from the process, depending on the cutting conditions, which serve as learning data for the ANN structure. They describe, that the model should be applicable for practical cutting in such a way that the predicted values of surface roughness could be a sign to adapt the cutting parameters in order to achieve the required surface quality or to detect disturbances in the process (tool wear, unfavorable chip shape, lack of coolant). In the introduction they also draw attention to the lack of adequate sensors and stated that the sensing technology will play an important role in the development of future manufacturing systems.

Further investigation of our monitoring concept for finish machining processes was therefore oriented to the search for reliable sensing. Some of the results of the use of so called AE-jet sensor were discussed at SEM and CIRP conferences. The main advantages of this sensor were presented as improvements of the signal to noise ratio, simple upgrade and the fact that the cutting process and sensor are not reciprocally disturbed. Through the spectral analysis technique and with adequate averaging procedures they could therefore find some useful information for the further development for the monitoring model.

In the paper the latest results of sensing the cutting process on the basis of AE signals and some particularities in further development of the monitoring model for the finish turning process will be presented. Using the experimental data of AE signals, obtained with cutting

under the favorable and unfavorable conditions, we have built up a new concept of monitoring decision-making. We varied the cutting speed, feed and depth of cut in such a way, that the center presents optimal values regarding the roughness, however at the limits roughness increase. Adequately, the response of the AE signals also change. We will discuss the question of accurateness of predicting the surface roughness on the basis of AE. The main problem, the overlap of the results, is presented by the same values of roughness or AE for different cutting parameters. This mutual interdependence of the data requires special procedure for building a neural network model. The final aim of such approach will be presented as improvements in learning or considerably reduction in error prediction. Further development of the monitoring model will be therefore presented in the sense of building a so-called intelligent sensor, which is able to perform the signal conditioning and feature extraction process.

2. THE ASSIGNMENT FOR MODELING: DETERMINATION OF SURFACE ROUGHNESS

The dependencies among parameters of the cutting process are very complicated, often unknown. In spite of unknown dependencies the engineer has to control the process e.g. select the appropriate cutting parameters. A model of the process has to be built up to satisfy this requirement. Artificial neural networks (ANNs) are efficient tools of model building if the dependencies between parameters are unknown. The roughness of the machined surface is a crucial factor in customer point of view. In this market push results that the engineer has to control also this parameter, consequently, a model is required to handle dependencies between the control parameters and the surface roughness. There are already some models, usually in form of functions, describing this dependency but these models are too rough, the real connections between control parameters and surface roughness are unknown. This shows that experts know that there are connections between these parameters but they are unknown. Several things influence these connections, e.g. machine, material, cooling, temperature, tool and other parameters, consequently, a model with high adaptivity is required. This requirement offers the reason to use ANNs as cutting models. In investigations presented in this paper the results of ANN model building for estimation of the surface roughness are described. The ANN building stage requires a training data set. To estimate the surface roughness parameters describing the energy content of the AE sensor are used beside the three machining parameters namely beside the parameters of depth of cut (a), feed per revolution (f) and cutting speed (v). Four parameters related to different frequency range are used to describe the energy content. The frequency ranges were:

1. for E_1 : 50-750 [kHz]
2. for E_2 : 99-249.5 [kHz]
3. for E_3 : 249.5-400 [kHz]
4. for E_4 : 400-610 [kHz]

The non-linear dependencies among these parameters are experienced, consequently, an ANN model can be used to realize the mapping among

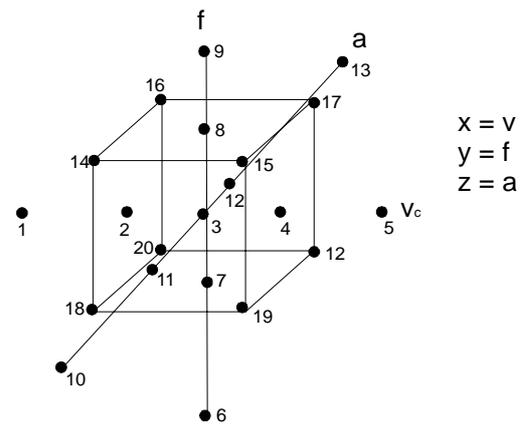


Figure 1. Machine parameters used to build up the ANN model. Parameters are in the range of cutting speeds from 100 to 500 m/min, feeds from 0,01 to 0,20 mm/rev and depths of cut from 0,1 to 1,2 mm

parameters. The above-described method was used to the automatic input-output configuration of the applied ANN model. Twenty-one measurements were used to build up an ANN model. The parameter ranges of selection of machining parameters are presented in figure 1. Seven machining situations were used to test the behavior of the applied ANN model. Machining parameter range of the test situations is presented in table 1.

Table 1

| Exp. No. | v_c | f | a |
|-----------------|-------------------------|-----------------------|-----------------------|
| 1 | 300 | 0,07 | 0,5 |
| 2 | 200 | 0,07 | 0,5 |
| 3 | 400 | 0,07 | 0,5 |
| 4 | 300 | 0,04 | 0,5 |
| 5 | 300 | 0,10 | 0,5 |
| 6 | 300 | 0,07 | 0,2 |
| 7 | 300 | 0,07 | 0,8 |

3. ONE OF THE MAIN PROBLEMS: OVERLAPPING

Outlying the multidimensional and non-linear nature of the machining operations and the fact that closely related assignments require different model settings, Viharos *et al.* [5] addresses the problem of automatic input-output configuration and generation of ANN-based process models with special emphasis on modeling of production chains. In this paper an algorithm is presented to build up a general ANN model through automatic selection of its input-output configuration. The algorithm does not have any regard to the given assignment of engineers its target is to satisfy the accuracy requirements. The following three tasks are solved with help of the developed algorithm:

- Determination of the (maximum) number of output parameters (N_o) from the available N parameters which can be estimated using the remaining $N_i = N - N_o$ input parameters within the prescribed accuracy.
- Ordering of the available parameters into input and output parameter sets having N_i and N_o elements, respectively.
- Training the network whose input-output configuration has been determined in the preceding steps.

This new method was used also for the given turning operation, too. The given parameter set consists of eight parameters:

1. Cutting speed (v)
2. Feed (f)
3. Depth of cut (a)
4. Energy content of the AE signal in the first frequency range (E_1)
5. Energy content of the AE signal in the second frequency range (E_2)
6. Energy content of the AE signal in the third frequency range (E_3)
7. Energy content of the AE signal in the fourth frequency range (E_4)
8. Surface roughness (R_a)

The applied ANN has to determine the maximal number of parameters, which can be estimated with the given accuracy and it has also to select them. As result this search algorithm gives the general ANN model of the operation.

4. ESTIMATIONS OF MACHINING PARAMETERS

Monostori&Viharos presented a method for solving different assignments of various levels and stages of machining with the general ANN model [3][2]. This algorithm searches for the unknown parameters of the general ANN model without having any regard to the input-output positions of them.

Because the number of learning vectors is small first we tried to build up an ANN model with one hidden layer and two hidden nodes. The target average estimation accuracy of the ANN model was +/- 2.5%. The above described method found one output parameter that can be estimated by the ANN model based on the remaining parameters (inputs). This was the E1 parameter (50-750kHz). The roughness becomes to input of the model.

Figure 2. shows the input-output configuration of this ANN model. With the help of the new method described above it is possible to estimate the unknown parameters based on values of known parameters without regard if it were input or output of the ANN model. This estimation was performed to estimate the roughness based on known values of v, f, a, E1, E2, E3, E4. The seven test situations were considered at first. By each of the situations the estimations were repeated ten times to check if there were more solutions for the given estimation task. Figure 3.

shows the estimation of roughness with this ANN model. Estimations are not very accurate but the developed algorithm reports through the E1 parameter that the roughness can't be estimated accurate enough. Similar were the results by the estimations of the situations, which were used to build up the ANN model. This concludes that the ANN model is not appropriate, consequently, the number of input nodes is to be enlarged. The second investigations were performed with an ANN having six hidden nodes. In this case the input-output configuration of the resulted ANN was different from the previous one. This ANN has five inputs and three outputs as presented in figure 4. Outputs are E1, E2, and E4. To check if the model is accurate

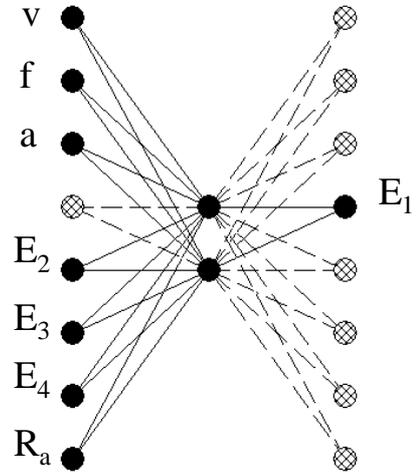


Figure 2. The resulted ANN configuration with two hidden nodes and with the allowed estimation error of +/-2.5%. E₁ is the only one output of the ANN.

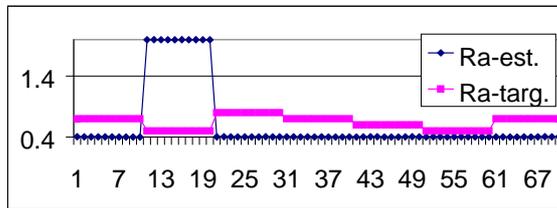


Figure 3. Ten times repeated roughness estimation of the test data. On the horizontal axis estimations from the first to ten represent the first test situation from eleven to twenty the second and so on. In the figure the estimated (est.) and also the measured (targ.) roughness values are shown.

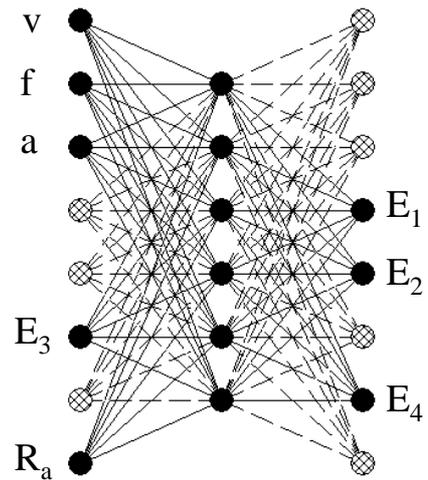


Figure 4. The resulted ANN configuration with six hidden nodes and with the allowed estimation error of +/-2.5%. It has three outputs and five inputs.

enough tests for roughness estimation were performed on the learning data set. Results of these estimations show that the ANN model learned the dependencies between the inputs and outputs of the learning data set. For testing the model in the test cutting situations roughness estimations were performed with this new ANN configuration again ten times for each of the situations. Figure 5. shows the estimated and the measured roughness values. The ANN reports again that it is not able to estimate the roughness in these situations but this ANN model could estimate the learning data set perfectly. This shows that in further investigation the number of learning data has to be enlarged.

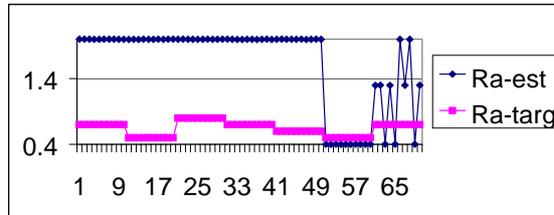


Figure 5. Ten times repeated roughness estimation of the test data. On the horizontal axis estimations from the first to ten represent the first test situation from eleven to twenty the second and so on. In the figure the estimated (est.) and also the measured (targ.) roughness values are shown.

5. CONCLUSION

In this paper an application of ANN models are presented to estimate the roughness of a given finishing operation. The approach uses the acoustic emission sensor as an information source to improve the estimation capability of the ANN model. Building up the ANN model to avoid the problem of overlapping and non-invertible dependencies used a new approach. The model was built up and the roughness was estimated but further experiences are needed to improve this research using a larger number of training data.

6. ACKNOWLEDGEMENT

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