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MODELLING OF DIFFERENT ASPECT OF THE CUTTING PROCESS BY USING ANNs

Abstract. In addition to developing novel ways of part formation (e.g. for the purpose of rapid prototyping), cutting remained one the most important manufacturing technologies [2],[11]. Though being the traditional way of manufacturing, the exact description of cutting processes is unknown, i.e. there are no comprehensive analytical models available for them [11]. However, today's measuring and process technologies allow measuring the important process-related signals with high sampling rates. Consequently, it is possible to build up a database from the collected data and to produce appropriate process models by using novel technologies, such as artificial intelligence (AI) techniques.
AI techniques have found their application in nearly every field (design, planning, control, optimisation, etc.) of manufacturing [6]. Artificial neural networks (ANNs) can handle strong non-linearities, large number of parameters, missing information and the relationships between various parameters [5],[9].
The cutting operation is very complex, therefore cutting is one of the typical fields of ANN based process modelling [5]. ANN was used to find hidden relations in the set of cutting-related data as presented in [7], [8], [12].
In the investigations to be described in the paper, the turning process was selected to analyse because of its relative simplicity. Different cutting situations were generated by adjusting machining parameters (variations of feed rate, depth of cut, cutting speed and cutting diameter) and measuring some physical parameters like force (3 dimension), surface irregularity, power, rubbing or built-up edge and temperature. Measured data were appropriately processed in order to generate a set of features for training the ANNs and some process related machining tolerances were determined.

1. INTRODUCTION

Reliable process models are extremely important in different fields of computer integrated manufacturing. They are required e.g. for selecting optimal parameters during process planning, for designing and implementing adaptive control systems or model based monitoring algorithms.

In the CIRP survey on developments and trends in control and monitoring of machining processes, the necessity of sensor integration, sophisticated models, multimodel systems, and learning ability was outlined [10]. Attaching further importance to the issue, in 1995 the CIRP Working Group on Modelling of Machining Operations was established "to

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promote the development of models of chip removal operations by defined cutting edges with the aim to quantitatively predict the performance of such operations, and to promote the use of such models in industry" [11].

Difficulties in modelling manufacturing processes are manifold: the great number of different machining operations, multidimensional, non-linear, stochastic nature of machining, partially understood relations between parameters, lack of reliable data, etc.

A number of reasons back the required models: design of processes, optimization of processes, control of processes, simulation of processes, and design of equipment [11].

Artificial neural networks (ANNs), neuro-fuzzy (NF) systems are general, multivariable, non-linear estimators, therefore, they offer a very effective process modelling approach. Such soft computing techniques seem to be a viable solution for the lower level of intelligent, hierarchical control and monitoring systems where abilities for real-time functioning, uncertainty handling, sensor integration, and learning are essential features [3]. Successful attempts were also reported on in the literature [1], [3], [4], [5], [6], [9], [13].

2. AUTOMATIC INPUT-OUTPUT CONFIGURATION AND GENERATION OF MULTIPURPOSE ANN-BASED PROCESS MODELS

Different assignments require different model settings, i.e. different input-output model configurations. Considering the input-output variables of a given task together as a set of parameters, the ANN model estimates a part of this parameter set based on the remaining part. The selection of input-output parameters strongly influences the accuracy of the developed model, especially if dependencies between parameters are non-invertable. At different stages of production (e.g. in planning, optimization or control) tasks are different, consequently, the estimation capabilities of the related applied models vary, even if the same set of parameters is used. Instead of different models with different set of parameters one general multipurpose model (Fig. 1.) is able to solve the same problems with higher efficiency.

The method for automatic generation of appropriate process models, i.e. models, which are expected to work accurately enough in different assignments, consists of the following steps:

- Determination of the (maximum) number of output parameters (No) from the available N parameters which can be estimated using the remaining Ni = N - No input parameters within the prescribed accuracy.
- Ordering of the available parameters into input and output parameter sets having Ni and No elements, respectively.
- Training the network whose input-output configuration has been determined in the preceding steps.

In order to accelerate the search for the ANN configuration, which complies with the accuracy requirements with the minimum number of input parameters, sequential forward search (SFS) algorithm is used. The search method is detailed in [12].

3. APPLICATION OF THE MULTIPURPOSE MODEL FOR VARIOUS ASSIGNMENTS

Because of the general nature of the multipurpose model, described in the previous paragraph, almost in every assignment, a part of input and a part of output variables of the model are known. During the solution the unknown part of the inputs and the outputs have to be determined by taking some constraints into account (Fig. 1.). Different known-unknown parameter settings (meaning different assignments) usually does not match the input-output configuration of the given, general ANN model, indicating, that a method is needed to determine values for the unknown parameters independently if they are inputs or outputs. A method was developed to solve this task as detailed in [7].

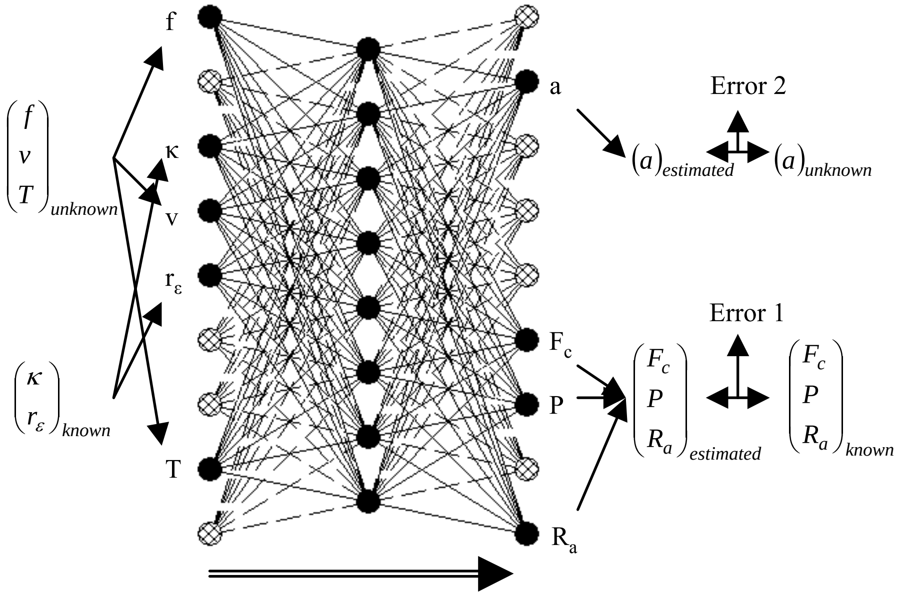

Fig. 1. The appropriate input-output configuration of the ANN based process model and the solution of an assignment determining the known-unknown state of the process parameters

4. Applying the concept for detecting process related tolerances

The way of application of the method described in previous paragraphs is non-trivial and has several prerequisites like software, know-how, etc. Another method for determining the appropriate tolerances for a given machining operation could be to perform experimental tests but this solution is usually more expensive and time consuming than the ANN based solution. Another reason is the speed of measuring, which is sometimes very slow, and requires high precision.

To solve the problem the following method was applied:

- The solution starts with the data collection. For the analysed cutting experiments, three parameters of the process were changed in a wide range (depth of cut, feed, and speed), five parameters were measured (cutting temperature, three dimensions of cutting force and surface roughness) and one parameter was calculated (specific energy of cutting – shows the cutting energy per chip volume).

- A wide range of parameters, calculated from the original measured values, is the result of the second step.
- An ANN based process model was built up having the above mentioned parameters on its input or output side. Seven process parameters were involved in the analysed model building process. As result the cutting speed, feed, depth of cut and specific energy of cutting become the inputs, temperature, surface irregularity and force became the outputs of the ANN model (Fig. 2.).

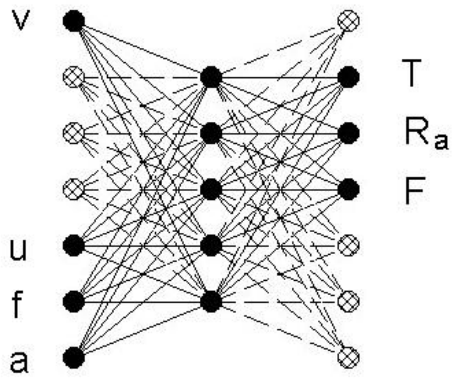

Fig. 2. The resulted general model of the cutting process

- Some thousands of possible solutions for the given manufacturing operation were determined using the technique reviewed in the previous paragraph, which applies the above mentioned general process model. This high number of solutions enables to represent and show the dependencies among process parameters learnt by the ANN model. The dependencies are shown through two-dimensional diagrams having different shapes and colours related to different parameter settings. Some selected diagrams are shown in the Fig. 3.

Solution zones in the Fig. 3. show not only several different, possible solutions of the given cutting process but also they outline the trends and nature of the dependencies among process parameters and the required parameter tolerances of different process circumstances, too. The nature of the investigated dependencies matches the ideas of engineers and the industrial observations showing that the introduced concept can be applied for determining parameter tolerances of different industrial processes.
Diagrams in Fig. 3. represent different dependencies:

- On the upper-left diagram the average cutting force and its dependence on the depth of cut are illustrated:
- As feed rate is increasing, the cutting force is growing.
- The cutting force is growing with the increasing depth of cut, too.
- On the upper-right diagram the surface roughness and its relation to cutting speed are shown:
- As the cutting speed is increasing the surface roughness is dynamic decreasing.
  - The surface roughness has a hump at the range of cutting speed from 30 to 90 m/min, with lower feed rate intervals.
- The dependence of the cutting temperature on the cutting speed is on the third diagram:

- With the growing of the feed rate and speed the temperature will be higher.
- As the cutting speed is increasing the rate of temperature rise is decreasing. This strengths the usage of high-speed cutting, too.

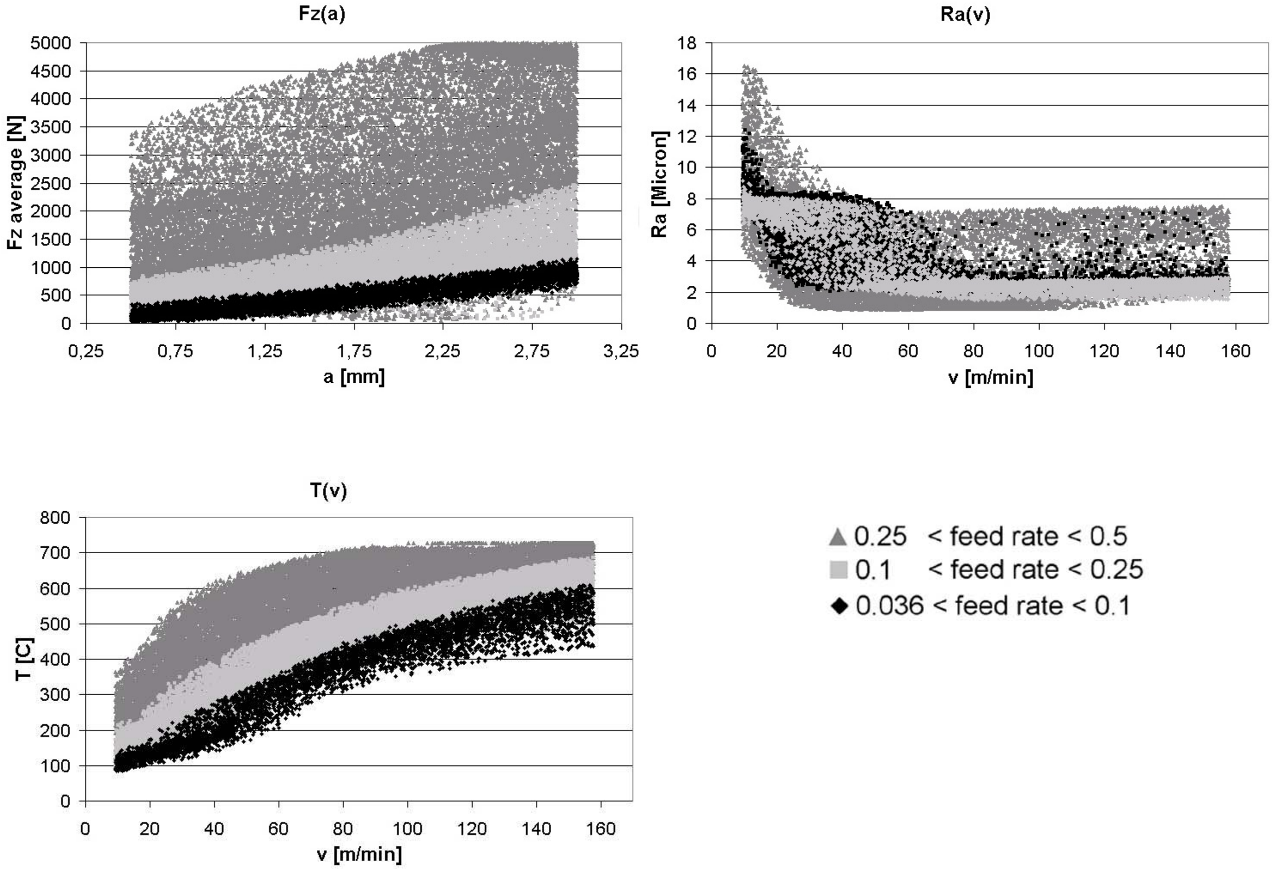

Fig. 3. Thirty thousand possible solutions of the analysed cutting process generated by the introduced method based on the ANN model of the process.

The way and the advantages for using these diagrams by engineers, could be evaluated in several viewpoints:

- In traditional way, these classic diagrams are the result of many expensive and long cutting and measuring processes. The proposed solution requires less measurements than in the classical way.
- One of the main problems of the technologist is: what is the optimal or almost optimal set of parameters that give the maximum performance? The engineer has to know the response of the cutting process in a wide range of various parameters to set optimal values for them.
- The applied materials and technologies are changing fast, there are strict time and money restrictions to determine the various diagrams. There are no reliable models for new materials, tools and technologies, consequently, the introduced combined learning-searching method could be used in novel circumstances.
- In our days the low cost and the maximum performance are the two most important things all over the word, of course in the industry, too. The usage of optimal parameters

is a key factor to reach these target functions and to remain in the market. The introduced method requires less financial background than to perform various test measurements. However, to build up ANN based models in the production are yet expensive because of the high price of the built in sensors and data acquisition devices. In spite of this fact, the spread of built in sensors and data acquisition systems can be observed in all fields of manufacturing. This fact strengths the application of the introduced technique, also.

5. Investigation of the effect of different input-output configurations of the applied ANN based process model on the parameter tolerances

As it is outlined in [12], the search method for building up the general process model determines the appropriate input-output configuration. The main target of the introduced search method is to identify the maximal number of output parameters that can be estimated within a predefined accuracy, consequently, this accuracy requirement can have influence on the input-output configuration. The resulted ANN model is applied to generate several solutions for different assignments using a search method as described in [7]. Naturally, this search method has also a predetermined accuracy limit for calculating the solutions, consequently, it influences the final solutions. These solutions are used in determining parameter tolerances for different production situations, as described in the introduced new concept of the previous paragraph. Summarising at least two factors influence the determined parameters tolerances:

- The estimation error limit of the search method generating the ANN based process model.
- The accuracy requirement of the search method used for generating several solutions of a given assignment.

The second search method uses the result of the first one, consequently, both of the errors arise in the final solution, namely in the determined tolerance limits. The effects of the first error limit on the tolerances were analysed recently.

The so called “max. estimation error” was used for measuring the accuracy performance of the ANN model. This error is the average error of the *worst* estimated output parameter. Less is the max. estimation error, better is the estimation accuracy of the ANN model. This paragraph details the first results without ending in a complete solution for this appointed problem.

During the first investigations, four configurations of ANNs were built up and the tolerance limits for the same assignment were determined and compared. The analysed cutting process was the same as in the previous paragraph. Four diagrams relating to four different ANN models were painted representing the same tolerance limits as shown in the Fig. 4. The selected diagram shows the effect of depth of cut on the cutting force in various intervals of feed rate.

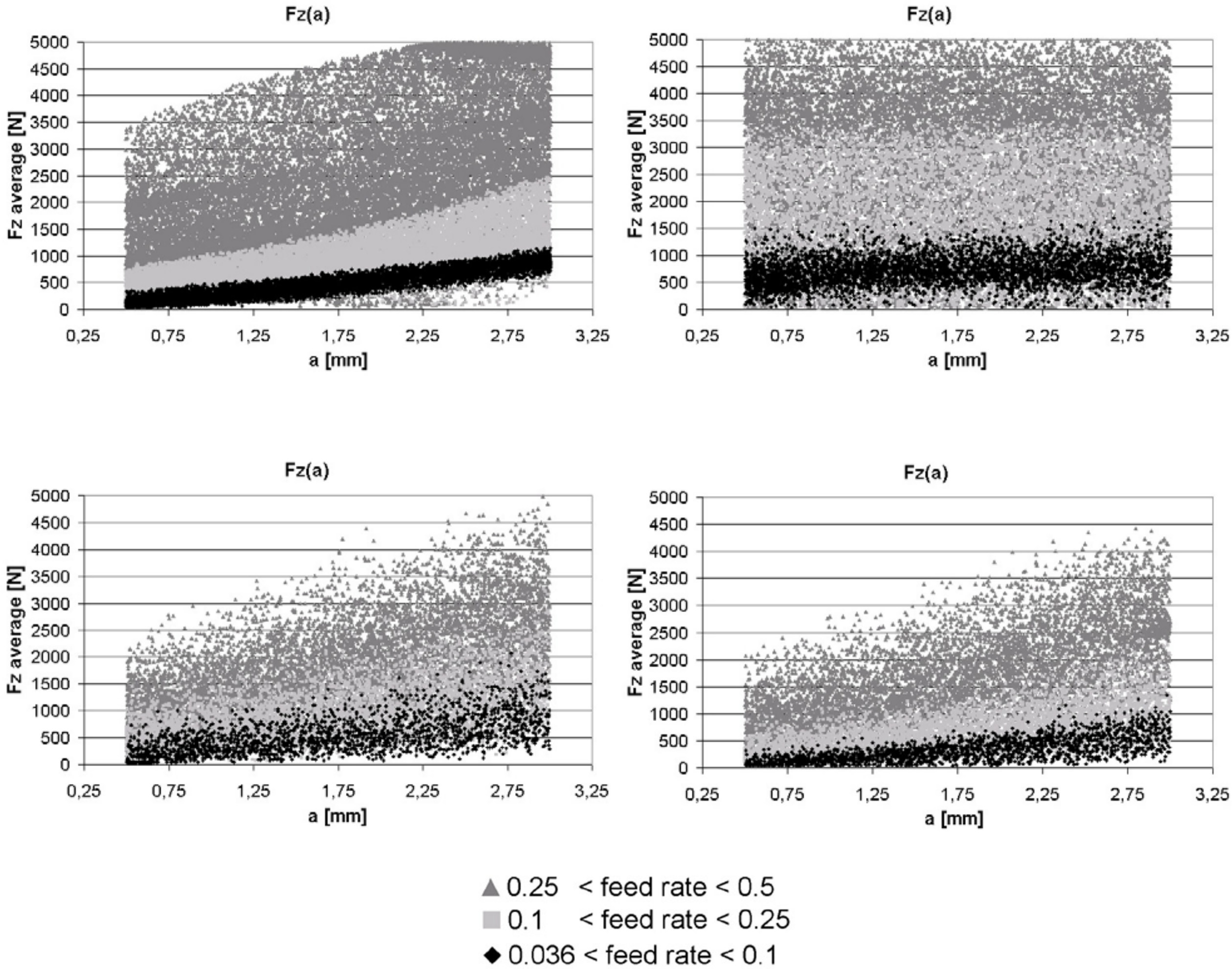

Fig. 4. Thirty thousand possible solutions of the analysed cutting process generated by the introduced method based on four different ANN models of the process

The diagrams were generated under the following circumstances:

- The upper-left diagram was the same ANN model as in the previous paragraph. Three outputs were the cutting force, temperature and surface roughness. The max. estimation error of the ANN was 12.79%.
- The upper-right diagram was created using an ANN model having the specific energy of cutting as only one output. The ANN learned the patterns and showed good accuracy on the set of test data (8,22%).
- When the cutting force was the only one parameter on the output, the ANN gave the best accuracy (2.66%) as presented in the bottom-left diagram.
- The last analysed configuration was, when temperature and average cutting force are on the output. The max. estimation error of the ANN was 4,93%.

The experiences from the diagrams can be summarised as follows:

- The effect of different feed rate intervals can be well identified in all of the cases, but the numerical values of tolerance limits are slightly different.

- The dependency between depth of cut and force is appropriate in three from four diagrams. The ANN having only the specific energy of cutting, as the only one output did not learn the required dependency between these two parameters.
- Known dependencies among cutting parameters were not learned by the ANN in some cases. This phenomenon was also detected during analysing other dependencies and diagrams.

Two very exciting questions arise, too:

- What is the better way to find the most accurate final solutions of a given task:
  - to have more output parameters with higher level of estimation error, or
  - to have less output parameters and enjoy a more accurate ANN process model?

  This question can be asked as in following, also: Where is the optimal point to add a new output parameter but to give up some accuracy of the ANN model?
- What is the effect of the errors occur in ANN learning and in the second search method on the final error of a solution?

These problems represent targets of the future research work of the authors.

6. CONCLUSIONS

The paper described a concept to determine parameter tolerances for machining processes. An experiment form the cutting field was performed and the results were analysed. The developed method was able to build up a general process model and to generate a huge number of different solutions for various engineering assignments with miscellaneous restrictions. Machining parameter tolerances come out through representing these solutions by diagrams as in the figures above. Finally, the effect of the selected input-output configuration on the accuracy of the identified tolerance values was analysed and some aspects of further research work were also highlighted.

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